PREDICTION AND ANALYSIS BASED ON SENSOR NETWORK DATA USING MACHINE LEARNING TECHNIQUES

Thesis for the Degree of Doctor of Philosophy (PhD)

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Debrecen, 2021

Hereby I declare that I prepared this thesis within the Doctoral Council of Natural Sciences and Information Technology, Doctoral School of Informatics, University of Debrecen in order to obtain a PhD Degree in Informatics at Debrecen University.

The results published in the thesis are not reported in any other PhD theses.

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I also declare that the results published in the thesis are not reported in any other theses.

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signature of the supervisor

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Dissertation submitted in partial fulfilment of the requirements for the doctoral (PhD) degree in computer science

Written by Ashraf Khaled Abd Elkareem Aldabbas certified in computer science

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(Informatics Systems and Networks)

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To the souls of my mother Mariam and brother Mutasem, my father Khaled, my family, and my princess daughter Lamar who have always encouraged me to pursue the things I love and care about and supported me tremendously in all of my honest endeavors.

Contents

List of Applied Abbreviations

AACS	Attitude and Articulation Control Subsystem
Al	Artificial Intelligence
ANN	Artificial Neural Network
Bd	Big data
Bi-LSTM	Bi-directional Long Short-Term Memory
CDF	Cumulative Distribution Function
CED	Complex Event Detection
CEP	Complex Event Processing
C-H	Cassini–Huygens
CIa	daily comfort index
CId	daytime comfort index
CO	Cassini Orbiter
CPU	Central Processing Unit
CKE	Constructive Knowledge-based Event
DL	Deep Learning
DNNS	Deep Neural Network System
EM	Equinox Mission
ESA	European Space Agency
FN	False Negative
FP	False Positive
GIS	Geographic Information System
GPUs	Graphical Processing Units
GRU	Gated Recurrent Unit
HGA	High Gain Antenna
HP	Huygens Probe
IoT	Internet of Things
ISA	Italian Space Agency
ISS	Imaging Science Subsystem

LGA	Low Gain Antenna
LMR	Layered Map-Reduce
LSTM	Long Short-Term Memory
MCC	Matthews correlation coefficient
ML	Machine Learning
NASA	National Aeronautics and Space Administration
NLCD	National Land-Cover Database
PDF	Probability Distribution Function
PI	Principal Investigator
RNN	Recurrent Neural Network
RPWS	Radio and Plasma Wave Science
RS	Remote Sensing
SED	Special Event Detection
SM	Solstice Mission
SOI	Saturn Orbit Insertion
SRMU	Rocket Motor Upgrade
SRU	Stellar Reference Unit
SVM	Support Vector Machine
TCI	Tourism Climatic Index
THI	Temperature-Humidity Index
TN	True Negative
TP	True positive
UTC	Coordinated Universal Time
VIMS	Visible and Infrared Mapping Spectrometer
VVEJGA	Venus-Venus-Earth-Jupiter Gravity Assist
wCEL	weighted Complex Event Level
WPS	weighted Extreme Pattern Score
WSN	Wireless Sensor Network

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Abstract

Sensing data remotely is getting more detailed and with smaller expenses now. Consequently, events may be detected offline or in real-time and fed into applications such as preparation, policymaking, natural hazards, environmental events, temporal based weather comfort, and emissions automatic monitoring and alert systems. In recent years, developments in wireless sensor networks and the Internet of Things (IoT) have allowed users to track the environment in even more high-resolution information. Air quality control and weather comfort are achieved by way of a distributed sensor network.

Science and development programs involving dynamic structures are mostly conducted in cooperation with different institutions, engineers, and scientists. Various sections of the framework are built by multiple organizations situated in other geographic locations in such a partnership. Interest in Machine Learning (ML) based science and engineering methods have recently grown rapidly. This increasing enthusiasm stems from the joint production and usage of effective algorithms for analysis, the vast volumes of data accessible from experimental instruments and other sources, and the accomplishments recorded by researchers and the academic community. Contemporary ameliorations in the sizes of the gathered data by outer space expeditions have created the needed space for innovative analyzing and classification models. In this dissertation, structured ML prediction is considered and precisely, those involving sequential structure. It is focused on the relatively mature methods of Complex Event Processing (CEP), which is associated with the identification of complex events focused on domain specialist rules and trends, while the meta-learning LSTM and Constructive Knowledge-based Event (CKE) algorithms can provide better analyses of vast volumes of data within a small-time interval and supervised learning via structured machine-learning prediction. This dissertation focus on the specific issues prompted by structured outputs when the object involved in a ML task has a CEP, prediction, or multi-class classification where the goal is to predict several outcomes from some set to an instance. I present our structured ML approaches to learning specific similarity measures for change-point detection.

Analyzing the environmental and interplanetary trajectory is a big part of the research tasks as rapidly linked tools, and sensory devices become part of our everyday lives. The high-velocity knowledge flow sea is rising. This vast amount of high-rate data generated demands rapid insight in numerous applications such as the IoT, energy storage, etc.

This produces the need for CEP frameworks, utilizing articulate state-of-the-art approaches to collect qualitative details. The Mission of Cassini, as an illustration, generated more than 630 gigabytes of research-based data that include 450,000 taken images. ML assists the experts and researchers with data enclosed by this vast extent. This dissertation uses the Cassini dataset as a particular instance of analysis to illustrate the remarkable capabilities of introducing Artificial

Intelligence (AI) among space missions to extend further intelligent computing. It is intended to consider exploiting Deep Learning (DL) on the space mission's evolution platforms, offering higher efficiency and reliability. Using DL classifiers with diverse data volume access, it is illustrated that incorporating the collected spacecraft data with machine-learning approaches, which is fundamental for obtaining scientific significance.

Based on these findings, the provided models on incorporating space sensed data into AI scope earmarking supervised classification concerning planetary data, which expresses a path incorporating Cassini spacecraft mission data into ML. The techniques of DL can be utilized to evolve intelligent solutions. Over the past several years, massive progress in AI techniques with special attention on neural networks has appeared globally. There has been a generous dash in the AI scope to provide robust solutions in numerous fields. Models focused on RNN with Long Short-Term Memory (LSTM), Bidirectional LSTMs, and Gated Recurrent Unite (GRU) are exceptional in learning sequences and capable of capturing long-range dependencies in the temporal data collection. In this analysis, various LSTM and Gated Recurrent Unit (GRU) models are used to model the Cassini–Huygens' outer space mission. The "learning" particular aspect of ML indicates the potency of an algorithm to detect data patterns to enhance the results, i.e., to utilize the available data to inspect and predict the unrenowned. ML so far has many implementations in video surveillance, online banking, aviation, product recommendations, and so on. Moreover, the technology is anticipated to leverage future space exploration since it can process massive data volumes, foretell spacecraft status, and detect patterns in the analyzed images. ML could empower cost-effectiveness, science profit, and dependability of missions in outer space.

This work employs environmental and planetary mission datasets to build creative classifiers. It is also demonstrated that amalgamating the generated spacecraft data facilitates ML approaches performance and delineation, which is fundamental for obtaining systematic purport. Based on these accumulations of findings, an approach amalgamating space generated data into ML methods designating supervised classification within the scope of planetary data context. These reached results provide a footpath for analyzing environmental data and incorporating data of planetary missions and DL algorithms to grant the computers the ability to impart data to create categorize and predictions swiftly and with high accuracy. A cutting-edge predictive CEP system has been established that use historical knowledge to diagnose unique and complicated incidents. To use historical knowledge effectively, the method uses N-dimensional, historically matched sequence space. The prediction may then be made by addressing the set of queries over historical sequence space.

This dissertation seeks to apply AI to determine which results will fit a given task. However, I am not investigating various types of AI methodologies, instead I am using these efficient solutions to identify specific phenomenon of the systems I have studied.

Chapter 1: Topic and context

This introductory chapter address several aspects such as the dissertation novelty and contribution, problem statement and motivation, research hypotheses. Also, it provides a preface for the aspect of IoT, CEP foundations, besides event detection and Remote Sensing (RS) contexts. These fields are anticipated to have a significant influence in numerous fields. Recently, curiosity in science and engineering ML-based methods has grown exponentially. ML increasing excitement stems from the combined creation and usage of robust algorithms for data analysis; vast volumes of data accessible from experimental tools, experimental computations, and other sources; developments in high-performance computing; and the achievements recorded by business, academics, and science. A typical notion of ML requires teaching an algorithm to automatically locate patterns, signs, or forms that may be concealed within large data sets of an undefined nature and thus cannot be configured directly.

1.1. Overview

Advances in technology have facilitated the convergence of connected ecosystems in different contexts, triggering event-based apps to assist users in their daily tasks. For instance, smart buildings/cities. Made it easy for everyone to work better in a healthy and more relaxed climate. The RS of the environmental aspect is a testament to the growing use of RS to manage natural resources. As a consequence, RS technology has the capacity to have consistent metrics that can be utilized. Besides, long-term change detection outcomes could offer insight into the stressors and drivers of transition, eventually enabling intervention strategies based on the cause rather than symptom through recognizing triggers of stress and acting upon them. With RS technology being more widespread, administrators need to provide a significant concern for RS professionals to introduce monitoring systems focused on the identification of shifts from remotely sensed results.

Climate has a powerful impact on the recuperation and tourism sector and its services. Many countries constitute the available resources on which the tourism sector and its services are predicated. Climate and weather have a major role in selecting the destination; due to tourist sensitivity to weather change. The awareness of climate parameters and their convenience for recuperation and tourism are essential knowledge about many potentialities for touristic activities. However, the circumstance of an individual climate parameter could not perfectly describe the climate conditions to specify the destinations for the tourists. The incorporation of planetary science in the ML method is a unique challenge. Domain information awareness may improve ML model consistency, interpretability, and defensibility of domain-agnostic results. Also, integrating science domain expertise can significantly minimize data requirements and improve testing and prediction. Spacecraft functioning in deep space will produce vast data amounts because of its mission complexity and various orbits and rotations that can be made. Conventionally planetary branch of knowledge has utilized gist scientific techniques like RS. Along with the contemporary attainability of sampled circumference data offered by such outer missions, the ML method provide remarkable capability preference. Exploiting ML in planetary missions varies from other prevalent implementations. Cassini's data generated by the orbiting Saturn system combines temporal and spatial extraordinary observations. This engagement requires (Spatio-temporal) complex events detection and in-depth analysis [1]. The extrinsic planets probe propelled 15.10.1997. The Cassini probe was a systematic program intended to accomplish a comprehensive and thorough examination of the Saturnian structure. It freed the Huygens scientific lander, which effectively put down on the Titan surface, which is Saturn's most giant moon. Following the Cassini insertion into the intended orbit around Saturn on 15 June 2004, the orbiter carried out exhaustive examinations of the magnetosphere, Saturn's atmosphere, and rings. Along with some Saturn moons. Engineering and scientists teams from Europe and the united states collaborated in the mission. The mission consists of transporting the Huygens probe, manufactured by the European Space Agency (ESA), to the Titan atmosphere. At the same time, Cassini's tasks include orbiting Saturn to acquire in-depth information about the planet Saturn and its satellites and moons. Cassini is the biggest interplanetary mission ever founded; it is 3-axis balanced. Orientation is preserved over the utilization of either thruster (with the purpose of path pointing and determination) or three reaction wheels placed over the spacecraft orthogonal axes. Cassini has gathered samples and sending them back to Earth; returned samples confer experts to exploits up-to-date technologies to enlarge the scientific value. Among the collected data, images are deemed the primary data source (see Figure 1.1).

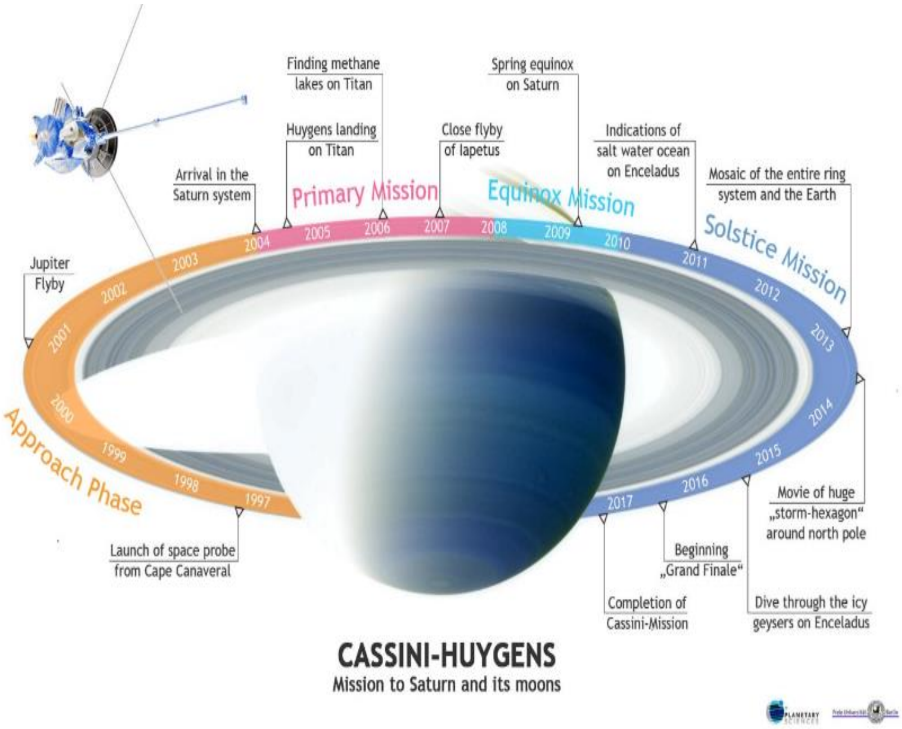


Figure1. 1: Mission phases of the Cassini-Huygens project (Source: Freie Universitat Berlin)

Orientation is specified over the exploitation of three inertial components of reference (utilizing the gyroscopes of solid-state) or by the star tracker unit that can recognize stars in its scope of scrutiny and matches an analogy between them and its onboard index of five thousand stars). These thrusters can likewise be utilized to perform trajectory modifications and corrections. The essential use of the acquired planetary data is to evolve the fundamental scientific hypotheses, which needs a particular potential to deduce significance from the implementations of artificial methods. As an effect, the ML scope is getting a significant part in examining the scientific standpoint [2]. There is specific attention to implementing interplanetary ML within this dissertation, which counts on specific domain prediction knowledge. Complexity relies on what comprises the general scope of knowledge. The scientist's role is to illustrate various models based on their field. This brings about a model that should be relatively unpretentious to be comprehended by their prediction procedure. The algorithm must bring forth an optimal explicable model for effectively dealing with computationally tricky issues. Significantly, the concepts regarding performance [3]. This work is interested in the interplanetary domain analysis to acquire scientifically insightful outcomes from the enforced ML models. The twofold defiance of Spatio-temporal generated data of spacecraft orbiting planets are constituted for the spacecraft data transmission and observation. A variety of data sizes establishing an approach to classify special and complex events within the Cassini dataset. Just as Saturn's distinctive data set and the ambiance of its surroundings, which provides exquisite perception toward applying detection and classification models into interplanetary data via ML, to acquire higher accuracy and interpretability of detected complex events.

1.2. Problem Statement and Motivation

Generating accurate results from RS data is quite challenging. Many factors cause this challenge, including the characteristics of an environment, the availability of proper RS data, adequate use of variables and classification methods, and the analyst's experience—advances in the algorithm and advances in techniques and principles. When applying ML methods, the data generated by remotely sensed devices offer a unique aspect, including special events, missing data, and Spatio-temporal sampling. It is indispensable to construct an interpretable approach that can learn meaningful information. One diffuse utilize of AI is to input an enormous quantity of raw data such as sensory data into the proposed model, enabling the algorithm to classify correlations among them. The framework concentrates on explicable supervised event detection among Cassini spacecraft generated data for the head aim of science inspection and analysis. The provided framework can be considered a guided implementation of feature extraction of spacecraft remotely sensed data, particularly for interpretability scientific insights.

The dataset of Cassini expresses a broad scope of sampled spatial-temporal changes in time data. Because of the spacecraft orbiting mode, assuring randomness, the datasets of training and testing are typically not adequate to produce prototypical data over time and space. For studies related to Complex Event Detection (CED), careful thought must be given to the datasets of training and testing independence to examine event data identification, including the Spatio-temporal part. Data from the Spacecraft orbiting process will produce hundreds if not thousands of characteristics. While specific ML approaches are intended for this category of knowledge, they usually do not generate suitable results for human understanding and empirical insight into the workings of physical structures. They convey a complex series of raw computation relationships that a kind of assistance to help people construct a viewpoint.

Science research focuses on two pillars: data collection, which utilizes computations, tests, and/or observations to produce new measures of complicated phenomena; and data processing, which seeks to derive new information from the data. Historically, much of the work has been to gather evidence, for example, beginning with the push to build telescopes to study planets and finishing with large-scale, multi-physics simulations to obtain a glimpse into potentially inaccessible processes, such as supernovae. Yet, where early research methods Ire basic as linear regressions, current strategies are increasingly complex blends of algebra, statistics, computer science, and various other disciplines for both studies and simulations. If the research method's sophistication has increased enormously, it is still primarily guided by human desires and hypotheses. Driven by their deep understanding, comprehensive knowledge, and Ill-honed instincts, scientists can build theories and customize empirical methods to validate or disprove them. As data size and sophistication grow, the risk of missed breakthrough opportunities may also intensify and will potentially impede development dramatically. To overcome this problem, several research fields shift. In the evolution procedure of complex systems, interdisciplinary teams of scientists and engineers are engaged. Frequently, such teams are established by inter-institutional collaboration. ML has become increasingly common in recent decades, mainly where large datasets are available. Creating a model using an ML approach requires learning a simplified model from the training collection.

Thus, the training set must be broad enough to construct a generic model from it, which performs Ill with the test process's unseen data. Training such models will cost computationally. But, once qualified, they work quickly in the implementation process. However, thanks to fast Central Processing Units CPUs and Graphical Processing Units (GPUs) availability, computing costs are no longer a concern. Different academic papers show a concrete proof of ML algorithms [4-5] success in pattern detection, time series estimation, data clustering, and classification. In this research analysis, outer space mission modeling is conceived as an issue of time-series prediction (temporal sequence modeling), so the ML algorithm can be implemented. In such a formulation, occurrences and their complexity function as triggers and, therefore, collectively determine the device's state, and sensor values are the resulting consequences. Because studies are performed over a duration, the duration is a significant consideration. Hence, this study's problem-space lies in exploring state-of-the-art ML algorithms for temporal sequence modeling. More data-driven approaches eventually seek to eliminate the need for assumptions and replace them with meticulously tailored theories with extensive data collections. This data explosion is not restricted to research applications. Digital revolution and the accompanying capacity to record anything, from banking transfers through internet sales and social networking communications, have revolutionized ML. This revolution was propelled by the availability of massive, labeled data sets propelling the creation of modern ML approaches. These methods enable computers to conduct several challenging tasks. Systematic ML is a central component of AI and cognitive science that can be learned to increase or automate human abilities with scientific evidence and analytical research. Scientific ML will change science and analytical analysis. Investments in extensive data from science missions, tools for predictive modeling and algorithms, high-performance computing systems would allow breakthroughs and significant change. The cross-cutting design of ML and AI creates a clear motivation to devise a development strategy to optimize capabilities and systematic benefits. Incorporating a variety of DL models, from the unpretentious to the more sophisticated, in addition to differing datasets, will give insights into the essence of the data produced by the underlying spacecraft generated data. DL applications in space science and big data analytics are both the soaring focal point of data science. This set of methods has been confirmed to be competent to swift and enhance both essential and empirical research. I implement a comprehensive overview and examination of the most up-to-date research in this scope. In recent years, the obtainability of huge datasets incorporated with the amelioration in algorithms and the rapid development in computing potential drives a unique outpouring benefit in the ML domain. For the time being, ML algorithms are effectively utilized for prediction, dimensionality reduction, and classification tasks of big datasets [6]. ML has been evidenced to have the exceptional capacity in great domains such as image classification [7], speech recognition [8], self-driving cars [9], and many others. This dissertation aims to use AI to decide which outcomes are most appropriate for a specific role. I'm not looking into different AI methodologies; however, I'm applying these effective solutions to recognize particular phenomena in the frameworks I'm looking at.

1.3. Novelty and Contributions

The innovation of this work is the concept and specifications of event detection and the architecture of the overall workflow (from sensing and event extraction methods to operations and decision-making processes centered on derived events) as an objective for potential event detection research.

This dissertation innovation examines the application of DL algorithms to core big data analytics issues, motivating more focused analysis by specialists in these two fields. Recent advancements in data collection volume from planetary space missions have facilitated new data science techniques. Between 2004-2017, the Cassini project obtained hundreds of gigabytes of scientific evidence. ML may help scientists operate on this larger-scale evidence. This curiosity derives mainly from a need to use these applications to appreciate dynamic planetary structures better. Spacecraft missions cannot deliver data volumes to describe space conditions around planets. However, spacecraft mission data are fundamentally difficult to integrate, for example, the unique Spatio-temporal existence of sampling into ML models.

The goal of this study is to establish a suitable mapping between incorporating the collected spacecraft data with machine-learning approaches to reach efficient ML algorithm, which iteratively learns from data, enables computers to detect hidden insights without being guided to search for them. Besides event complexity processing, revealing, and analysis, which enables reliable estimates of classification performance. This study proposes a novel algorithm for detecting complex events in the Cassini spacecraft generated dataset for learning complex events data representations that facilitate new methods to simulation and data analysis across the associated research disciplines. This combinatorial algorithm is proposed using the newest efficient optimization methods. This part outlines this dissertation's analysis problems and contributions. The key concerns are whether CEP systems can manage higher volumes of data to identify complex events and implement smarter predictive features. This study focuses on two significant research challenges: high-performance CEP to identify complicated trends and predictive CEP. Finally, I adapted and reviewed our models tested on real-world data in international journals and conferences. This produced ideas that helped us further refine our algorithms. This dissertation compares the performance of the proposed algorithm concerning the existing other solutions. The major contributions of this thesis are as follows:

- Development of novel approaches that process remotely sensed data to detected air quality and climate comfort period.

- Much scientific research considering uni-level of CEP, while within our research I introduced the multilevel concept.

- A novel paradigm for recomputing CEP queries is provided. Our algorithms reduce complexity in space and time.

- A novel algorithm for classification where each intended task is a supervised learning issue like image classification. The purpose of utilizing LSTM networks to acquire an upgrade rule for neural network training during the feature's extraction.

- Overcoming low accuracy and ensuring optimal performance of supervised learning via structured prediction and meta-learning LSTM.

- Latest developments in DL have shown those sequence models, including

  LSTM or GRU are effective at classification and prediction tasks and the DL method of detecting trajectory modifications.

- One of the proposed algorithm's main features is that it needs no special controller and only standard optimizing parameters such as population size and the number of iterations involved in its implementation. Therefore, the algorithm least relies on the parameters.

- CEP is associated with the identification of complex events focused on domain specialist rules and trends. The meta-learning LSTM and CKE algorithms can better analyze vast volumes of data within a small-time interval.

- Using relevant information regarding events and their relationships in the application environment will enhance the expressiveness and versatility of CEP systems. Massive volumes of domain history information contained in an external knowledge base may be used in conjunction with event processing to accomplish a more competent, dynamic CKE.

- A systematic literature survey about CEP and the C-H scientific dataset, techniques, and algorithms in the related research domain.

- The proposed algorithms are viewed concerning the output comparison and assessment of other current algorithms.

This dissertation work resulted in six journal papers, eleven conference published papers, and one journal paper still being processed.

1.4. Research Hypotheses

Standard approaches of science research lead sequentially from gathering evidence to analyzing hypotheses that codify new knowledge. Using high-end computing for complex model assessment and data-driven approaches for model enhancement and optimization in recent years has significantly enhanced and accelerated progress along this route, establishing what is often known as paradigms for science exploration and innovation. A learning model develops a theory from a sequence of training examples, findings, and observations and then searches through the hypothesis space to move into an ideal hypothesis compatible with the examples of training and Ill above other unseen findings.

The success of the dissertation work depends on the completion of the hypothesis. The key hypothesis is split into tiny hypotheses. The theories are then indicated as follows:

- Model as abstract as practicable and as comprehensive as required.
- Modeling can be based only on data-space input and output and applied rapidly.
- The model will manage different forms of input and output signals: binary, persistent, step-like, repetitive, etc.
- When the unseen data is transmitted to the framework, the model shall be able to reproduce the framework in the test process.
- The model should not over-fit the training results and function effectively in the implementation process with the latest inputs.
- It is hypothesized that; approximate meta-learning LSTM, CKE, and structured prediction algorithms find optimal solutions with less computational effort than optimization algorithms, iterative methods, or simple heuristics.
- It is hypothesized that the establishment of balance among completion time and increasing efficiency is done using optimization methods.
- For the up-to-the-model, a threshold value should be established in which the prediction error may be predicted.
- It is hypothesized that; the proposed algorithm must be scalable and can be performed in polynomial time and ensures convergence to the optimal solution. This means that it does not stick in local optimums.

1.5. Used Datasets in the Dissertation

The below mentioned datasets are used by our research have been referenced and cited in peer- reviewed academic journals. These datasets are a central area of environmental RS and ML science. The common aspect among the used 3 datasets is that I'm aiming to detect, record, and process the changes among them all, the 3D road network (North Jutland, Denmark) dataset, climate comfort dataset, and Cassini-Huygens (C-H) mission dataset. I aim to detect the associations between environmental measurements or planetary factors and the spatial or temporal distribution of events across the datasets.

1.5.1. Environmental Datasets

There are two data sets involved in developing, adopting, constructing, and evaluating the related environmental data.

3D Road Network (North Jutland, Denmark) Dataset

The dataset was built by applying elevation details to the North Jutland, Denmark 2D road network (covering a region of 185 x 135 km^2). Elevation values Ire derived from a freely accessible point cloud of a laser scans for (North Jutland, Denmark) Figure 1.2 represents a google map view of the North Jutland region. The 3D road network was used to evaluate and refine different fuel and CO_2 calculation algorithms experimentally. Any applications that need knowledge of a road network's precise elevation details may use this dataset to do more precise routing for eco-routing, cycling paths, etc. Each sample attribute includes latitude, altitude, and longitude.

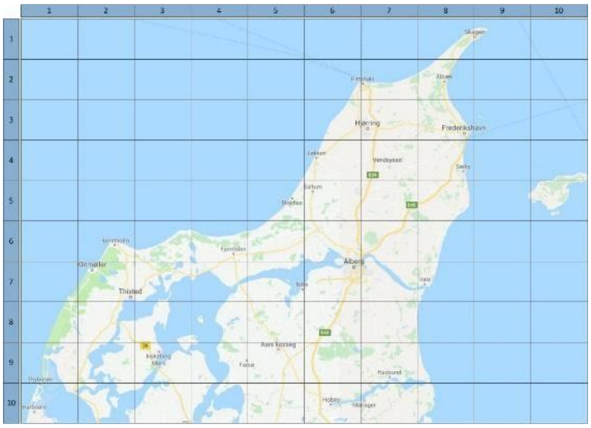


Figure1. 2: Denmark, North Jutland region Google Map view (Size: 185 km^2 x 135 km^2)

The spatial coordinates for this three-dimensional road data network comprise altitude, latitude, and longitude for each road section. At the UC irvine ML repository, this dataset is freely accessible [10]. The 3D Road Network has a total of 434,874 distinct data points without labels.

Climate Comfort Dataset

Two websites have been selected to acquire the needed datasets as they contain a huge volume of historical data. The purpose was to collect and integrate the elements of measurements for the obtained data, as this will minimize potential inconsistencies in the data and the process of analysis climate dataset include 1381 months climate time-series comprising precipitation and temperature for the period 1901-2017. The datasets Ire downloaded from climate change knowledge portal (The World Bank Group) website (Climatic Research Unit) of University of East Anglia) [11], and Iowa State University website (mesonet.agron.iastate.edu) [12], the second dataset is dedicated to being utilized to specify the Tourism Climatic Index (TCI) values over the last six and half years. Observation stations reported hourly measurements and are ordinarily provided by a professional crew. They frequently specified as having OJAI, OJAM, OJAQ, the A character symbolizes (for Airport) in their name, there adopted observation stations are: [OJAI] Queen Alia International airport station, this observation station is the middle station over the other two stations as shown on the given map on Figure 1.3.

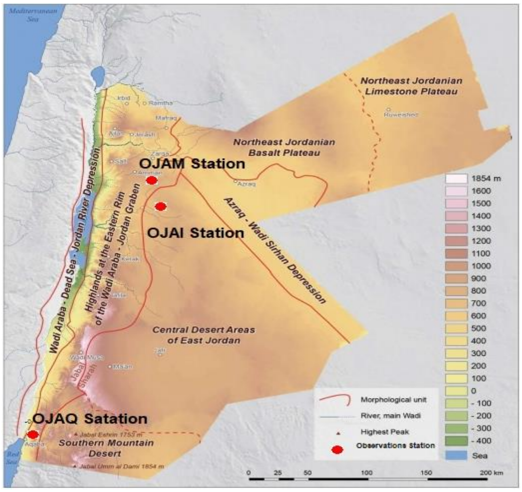


Figure1. 3: Topographic map of Jordan shows five main morphological zone

[OJAM] Marka Intentional Airport [Amman/king Abdullah], that is located nearby to the north, and [OJAQ] Aqaba King Hussein International Airport, which appears on to the south of Jordan area according to the map. The major features of Jordan's climate are in a disparity between a comparatively rainy period of time between November till April and have a dry climate for the rest of other months, with two tight metamorphosis seasons. Rain falls occur within the winter months only. The weather, mainly of the Mediterranean pattern, however, is relevant mostly to the high areas.

1.5.2. Cassini-Huygens Mission Data Set

Cassini mission data set has facts to explain better the spacecraft and project, the payload of the experiment, specifics of how data from each instrument can be found, calibrated, and interpreted, and tools to help learn further information regarding the vital research fields that have been explored throughout the Saturn system. The utilized Saturn EDR Data Sets (Volume 1 – Volume 116) can be found at reference number [13].

I validate the approach on the C-H mission dataset, which is purposed for public access and use. The Cassini spacecraft was launched on 15 October 1997 using a Titan IV / B launch vehicle with Solid Rocket Motor Upgrade (SRMU) strap-ons and Centaur upper deck. The spacecraft used a 6.7-year Venus-Venus-Earth-Jupiter Gravity Assist (VVEJGA) trajectory to Saturn, during which cruise observations Ire performed to verify, calibrate, sustain, and perform minimal research. After Saturn Orbit Insertion (SOI) (1 July 2004), the Huygens Probe (HP) detached and reached the atmosphere of the satellite after an approximately 150-minute plunge (14 January 2005). The Orbiter continued a Saturn system tour until mid-2008, gathering data on the world and its satellites, rings, and atmosphere. The Cassini Orbiter (CO) was a balanced three-axis spacecraft fitted with one High Gain Antenna (HGA) and two Low Gain Antennas (LGAs), three Radioisotope Thermoelectric Generators for fuel, main engines, attitude thrusters, and reaction wheels. It held twelve orbiter instruments planned to perform 27 research inquiries. The HP had six instruments to research Titan's atmosphere and earth. It reached the upper atmosphere covered by a heat shield and then deployed parachutes to descend from around 200 km to the surface steadily. After the successful prime phase, both resources and main spacecraft structures Ire healthy. NASA (National Aeronautics and Space Administration) Headquarters provided funds for creating a 2-year Cassini extended project due to the prime project's exceptionally efficient operation, the overwhelming amount of scientific observations, and the overall quality of research being returned by the Cassini spacecraft and the projected propellant left after the prime mission. After the prime mission phase tour on June 30- 2008, Cassini launched a two-year extended trip called the Equinox Mission (EM) to be concluded on September 30.

The CO can be defined as a three-axis spacecraft fitted with a single HGA and a double LGA, three thermal isotopes for fuel, main engines, motor assemblies, and reaction wheels. It holds twelve orbiter instruments planned to perform 27 research studies. The HP had six instruments built to research Titan's atmosphere and earth. It reached the upper atmosphere covered by a heat shield, then deployed parachutes to descend from around 200 km to the earth steadily. Tools with the acronym and Principal Investigator (PI) Ire associated with spacecraft body parts. The payload fairing protected the spacecraft during Cassini's launch, the first three minutes, and 27 seconds of operation, shielding it from intense sunlight. At 9 min 13 sec 206,700 m, the Centaur upper stage separated from the launch vehicle. The first centaur burn started at 9:13 sec and lasted almost two minutes. This burn put the Cassini spacecraft in an elliptical, the centaur shot again, launching Cassini on the path from Saturn to Venus. Directly after departure from the centaur, the Attitude and Articulation Control Subsystem (AACS) of the spacecraft aimed the HGA towards the Sun to obtain a thermally secure attitude where the HGA acted as an umbrella for the spacecraft. X-band uplink and downlink Ire developed via LGAs, Radio and Plasma Wave Science (RPWS)Langmuir Probe was deployed, instrument replacement heaters and main engine oxidizer valve heaters Ire switched on, and decontamination of the Stellar Reference Unit (SRU), Imaging Science Subsystem (ISS) and Visible and Infrared Mapping Spectrometer (VIMS) Ire initiated

The mission's Tour phase began when the Huygens test and orbiter support playback Ire completed and ended on 30 June 2008. It included dozens of satellite meetings and extensive observations of Saturn, its rings, and its particle and field environments. The prime project in Cassini was the most complicated tours ever flown. The extended mission retained the degree of architecture and navigational sophistication needed by the Cassini discipline working groups within 2,25 years to accomplish and reconcile the various disparate scientific objectives. The Solstice Mission (SM) is scheduled to dilate for seven years. With the restriction that periodic senior evaluations will be needed as the mission progresses. This project explores Saturn's system features, such as rings, magnetosphere, titanium, and icy satellites, particularly Enceladus. The planned end phase is called proximal orbits. This Juno-like mission gives Cassini major-specific scientific opportunities, including gravity mapping measurements, high-resolution ring observations, and in-house measurements of Saturn's atmosphere. The satellite will eventually be disposed of in Saturn's atmosphere on 15 September 2017.

1.6. Event Processing Scope and Detection Prerequisite

Event processing may generally be described as any framework that conducts event operations, such as reading, producing, converting, and deleting events. Reading activities to collect useful or beneficial knowledge and take behavior from them is the core concept of event processing. The core features of event processing systems include data filtering, aggregation, transformation, pattern recognition, pattern discovery, and pattern prediction. Non-functional criteria involve efficiency, reaction time, performance. Many applications have emerged in recent years that require the processing of large volumes of continuous data streams. These applications range from simple alarms to highly complex trading systems analyzing thousands of transactions per second. These applications have been implemented using ad-hoc solutions for many years, resulting in high operational and integration costs and limited reuse opportunities. This is the context in which CEP technology has emerged.

An event can be defined as an incidence of some substantive transition happening or expected to have occurred within a given structure or domain. An event could usually be two types: simple and complex. A simple event may be a transition event—where the value of a specific observable parameter varies from that of the prior measurement, e.g., an object's position—or a status event—where I notice the value of a specific parameter at a particular point in time, e.g., temperature sensor readings. In the complex event, the same parameter values may be called a meaningful adjustment based on the application at hand, e.g., the CPU's core temperature readings. A complex event is either a collection or a derivation dependent on several simple and/or numerous complex events. They are generated by event algebra operations, e.g., grouping, sequencing, or utilizing semantic awareness of several simple/complex events. The combined number of CPU temperature measurements over 15 minutes is an example of a composition-based complex event. On the other side, the assumption that the CPU fan is not functioning correctly, based on measurements of rising temperature measurements simultaneously, is an example of a complex event derivation-based case.

Spatiotemporal events are complex, adaptive, context-based [18]. Events derived from different data sources, such as sensory reading and images, are linked to the adjacent material's characters or disseminated to individuals and groups affected in spatial awareness [19]. Spatiotemporal events demand factual accuracy and consistency in content (i.e., if the event is true), place, and time to promote decision making. The task of event detection has varying timeliness or real-time criteria from seconds, minutes, days, and longer. For example, earthquake alerts are useful if they precede. Suspicious maritime events, such as arrival at critical points of a vessel trajectory, should be detected within seconds to enable action if necessary. IoT is a modern computing model where ubiquitous sensors and actuators installed in the physical world enable us to observe, control, and optimize the device's performance. IoT-motivated technologies cover cyber-physical services like smart water storage. IoT applications' main constraint is to apply analytics to data obtained from distributed sensors to render intelligent device management decisions. These requirements are also made on data streaming from edge devices at large input speeds. These analytics and decision-making might be time-sensitive and involve a low latency answer, as in a power system. Big data frameworks for streaming and CEP ensure consistent IoT analytics. They are designed to process data or event streams with low latency, e.g., sensing devices or social network streams. CEP is used to recognize threshold violations to cause warnings, accumulate incidents over temporal frames, or classify events with a particular interest pattern. The queries could be written as a matrix for decision-making in Sensor networks.

1.7. Complex Event Detection and processing in the context of IoT

Intelligent data processing improves the efficiency of underlying applications by knowledge obtained through sensors. Numerous (such as in many) applications are building upon wireless sensor networks (WSNs)to transform their sensing parameters into related system computations. Think of it as a vast number of identical sensing devices fitted with an interoperable radio.

The sensors are getting more capable of tracking bigger real-world environments, in several scopes. Perception of sensor data will require a significant amount of sensing instruments. This technology will generate a large amount of recorded observations. The main benefits of the sensor nodes over a wired solution are low cost and quick to deploy. Many researchers conclude that most of that WSN implementation is reactive or event-based. Rather than making sensors sample data regularly and sending out readings, users can wish to use sensors to record complex events of interest and detect the related events. Events only submit data as they arise. CED performs the jobs usually performed by bringing computation through the network. A real-world scenario is understood in a given way. A context describes a time interval within which it is essential to identify a complex event. Each context description refers to a collection of initiators, a group of terminators, and respective contexts. In this sense, triggers and terminators are the instruction writers, and the cross conditions happen on their behavior.

The mechanism that initializes (triggers) an operation-based event, representing the time at which the event is initiated when a context start occurs. Terminators may be either occurrence that arises directly after the initiator or a period span after the initiator. Events can occur at the same moment, and certain events can be responded to by other events. These instances should be reviewed to have unambiguous explanation requirements.

Sensor data, on its own, is relatively low-level and must be further processed, analyzed, and converted into more complex data to be useful to specific applications. For data-driven pervasive computing, users are involved only in the knowledge that comes from their sensors, which I term events.With the IoT to horizon devices connecting technologies. It needs the power, technology, and energy to link entities and networks that interact solely machine-to-machine, often over immense distances. With the continuous growth of the IoT applications, sensor networks connect the barrier between the outer-space world and the computing and networking virtual space. These sensors incessantly produce voluminous streams of heterogeneous data that require fast and predictable structures that often involve techniques to evaluate, process, and classify trends from numerous streams of events.

IoT data is data from time series where data is autocorrelated; due to their temporal operators, the CEP can handle it. Most IoT use cases are nuanced and go beyond aggregating results. CEP can be described as a composition of numerous simpler events, e.g., sensor readings, elementary shifts, updates, etc., that meet different temporal and causal relationships. CEP's potential for real-time computing is the key force motivating researchers to investigate it for IoT applications. CEP is an emphasizes to evaluate sensor data sources from various sensors and event streams in reasonably close. However, a synthesis of the two technologies may enhance event processing by using meta-data ontologies. The CEP paradigm has arisen where certain event management cases involve a high degree of expressivity, consistency, and simplicity. It has been developed to detect more complicated incidents, grouping events, clustering, and filtering utilizing a knowledge base.

IoT is a technological trend. It applies to a potential Internet, where various artifacts and positions are fitted with sensors and processors rendered accessible through the network and can interact with humans and each other [14]. In reality, such contact between human-unattended communication devices is a crucial innovation of the trend. The introduction of this technology lets people navigate the routine and seems appealing and promising.

Big data is at the core of analytics when it gathers organized and unstructured data from online apps, server reports, and social networking pages. CEP achieves higher, faster results. When analyzing, the challenge only increases as billions of sensors and tiny devices keep collecting further data. Event processing for sensors healthcare systems, especially IoT-based frameworks that include other patient and community data in real-time from medical devices, provides many advantages that minimize risk and improve patient safety as data is processed as it occurs. For example, if a patient's blood pressure or temperature is too high, they will know instantly. When I merge CEP and IoT, the window opens to customizable analytics. The two can be utilized to predict and perform critical responses when appropriate. The implementation of IoT technology [15] has made considerable progress with IoT technology advancement and the commercialization of high-performance IoT products [16]. Figure 1.4 represents the combination of the CEP and IoT.

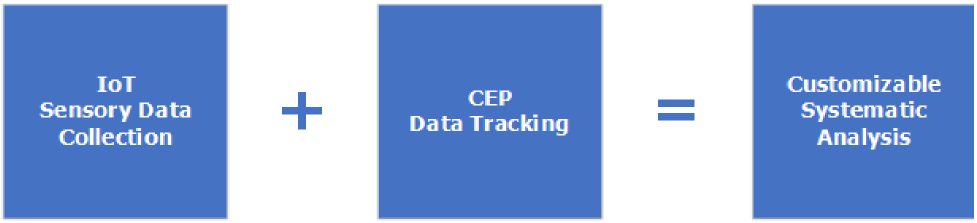


Figure1. 4: CEP and IoT Combine

The use of IoT technologies to increase the efficacy and accuracy is a new field of research. The IoT introduces a new generation of IT to hazard avoidance. It embeds sensors and installs equipment in appropriate locations according to requirements and incorporates the IoT with the existing equipment [17].

1.8. RS Connotation DL and IoT Integration

With enhanced space remotely sensed images, all-weather imaging increased spectral resolution, more informative and regular views, and smaller, cost-effective satellites, the RS of the Planet has been gradually improving. Events may then be monitored offline or in real-time and feed to applications like automatic monitoring and preparation alert systems, decision formation, natural hazards, environmental events, and emissions. Active sensors have simple, highly penetrated images that enable a better capturing of surface targets in almost all weather and daily life [20]. Many existing techniques for extracting events learn from historical events using statistics and probability of incidents and resources. Exploring irregular spatiotemporal variations in data streams or moving learning from current human-constructed case schemes to unseen occurrences. Future approaches and technologies require life-long learning capabilities where a device can continuously recognize current, unexpected incidents and apply these events to the knowledge base incrementally. Computer interactivity and DL approaches are rapidly critical. Computer and DL-based methods of event extraction with interactivity can improve human-machine coordination and correct early-stage errors. By comparison, explainability approaches may boost consumer trust for the detected incidents.

Furthermore, due to the immediate need for real-time answer and decision-making, new self-active learning, or even unsupervised learning methods with minimal training datasets and as little human annotation effort as possible, should be created. The drastic growth in data volume sensing needed high-performance computing resources for scalable event detection. Computational platforms, such as the ESA Ire built to fulfill this need. However, features for managing massive spatiotemporal data are not readily available regarding query optimization, preprocessing, and streaming of knowledge extraction from vast spatiotemporal data. Every event extraction issue can consider several different data sources of different styles and formats. Fusing data from different channels, such as multi-sensor, multimedia, is essential by aggregating, translating, and reformatting it into a standardized framework.

ML and IoT integration lay the groundwork for potential performance, precision, productivity, and overall cost reductions for resource-constrained IoT applications. ML algorithms and IoT function together to enable excellent communication and computational efficiency, better maneuverability, and better data. Due to integrated tracking of thousands of omnipresent sensing instruments and enhanced networking capacities. IoT has immense capacity to enhance life quality and to manufacture development applications. By converging intelligent automation, IoT's ability has dramatically increased. Advanced AI methods have made it easier to mine the vast amount of sensory IoT data for greater visibility into various real-world challenges and the potential to make important tactical decisions. Therefore, IoT and ML must supplement each other to solve complicated real-world challenges and effectively satisfy computing and connectivity requirements. In IoT data processing, ML algorithms perform an essential role [21]. With growing data volumes, the processes created or developed hour by hour by our own devices are not valuable unless processes for data processing such as big data are appropriately used. CEP is a central component of the (IoT). Proactive CEP will foresee potential device conditions and take steps to stop undesirable states, giving fresh optimism to IoT transportation [22].

Digitalization directs to growing quantities of data characterizing the events around us. As a result, CEP engages a central part in analyzing a multiple data stream. Structured prediction indicates a framework of ML, which predicts several inter-associated and reliant quantum. For CEP enforcement, a variance can be initiated along with the complex events, whose frameworks among data streams are recognized previously, and the one that is encountered for the 1st time. The special event's query language offers an appropriate method to appoint complex events and competently realize them. Structured result scope takes place in several ML enforcements that intend to label specific sets of affiliated variables to which the reliance among the factors that are liable to vary or change mandate what assigned task is applicable. Different sources of the data streaming and the IoT demonstrated Dynamic Event processing. The capacity to capture data from devices utilizing sensors, enhancing data carrier networks and the stable transmission to a centralized location has provided a jump to evaluate various data patterns from multiple devices in combination.

Chapter 2: Background and Related Work

Our dissertation deals with several issues emerging from ML from an overarching point of view. This research area seeks to derive meaningful laws from observed data that can be extended further to explain new data. This dissertation focus on the specific issues prompted by structured outputs when the object involved in a ML task has a CEP, prediction, or multi-class classification where the goal is to predict several outputs from some set to an instance. I present our structured ML approaches to learning specific similarity measures for change-point detection. This literature survey aims to identify different related issues in resource allocation, load balancing, and scheduling, such as algorithms, methods, and techniques in cloud computing, and identify areas for future research. Although many solutions were identified in this research, it has become apparent that much of the research being done only relates to the theoretical side of this issue. Thus, this review shows that however, many solutions and techniques have been identified, future research should focus more on the practical implications.

2.1. General Aspects of the Research Topic and the Literature

The advancements of sensing technologies, including RS, climate analysis, and health sense, have tremendously improved our capability to observe and record natural phenomena, such as temperature change detection over a long period of time and the detection of healthy residential district zones based on the air quality.

Classification of machine-learning has been a significant subject of remote-sensing literature [23-25]. Machine-learning algorithms are typically capable of modeling complex class signatures, accepting a range of input predictor data, and not drawing assumptions regarding data distribution (i.e., nonparametric). A wide variety of studies have typically shown that these approaches appear to be more reliable than standard parametric classifiers, especially for complex data with high-dimensional feature space, i.e., multiple predictor variables (e.g., [26-29]). Machine-learning methods have been generally recognized, as demonstrated by their usage of land-cover mapping. The 2001 National Land-Cover Database (NLCD) land-cover classification for the neighboring USA was developed using decision trees (DTs), Homer et al. [30]. Given the increasing adoption of machine-learning classifiers, parametric approaches still tend to be widely utilized in program papers and remain one of the primary benchmarking studies. For example, in a meta-analysis of more than 1600 papers analyzing remote-sensing classification methods, Yu et al. [31] showed that the parametric maximum likelihood (ML) classifier was the most widely utilized approach used in 32% of papers. At the same time, machine-learning methods Ire regularly found to have substantially higher accuracies than ML. [32] relate this superiority to ML's wide availability in traditional remote-sensing software packages and call for more software creation and training in machine-learning. Our anecdotal experience of remotely sensed data consumers confirms this claim. I find that questions on utilizing best and applying machine-learning strategies are the biggest obstacle that many application scientists utilize. Despite the vast number of remote-sensing research papers exploring ML for RS classification, these uncertainties remain.

Ghamisi et al. [33] give a recent analysis of advanced algorithms focused on classifying hyperspectral results, evaluating and illustrating several approaches' strengths and shortcomings. Nevertheless, a considerable debate of an applied viewpoint centered on utilizing these algorithms is not currently accessible in scholarly literature. Hence, this essay discusses machine-learning literature and examines functional issues on machine-learning classification for remote-sensing.

The principle of incorporating information into learning has had a long history. Historically, the two antipodal paradigms of symbolism and connectionism Ire roughly regarded by AI studies. The former was dominated by symbolic information up to and including the 1980s; the latter became more common in the 1990s, using neural networks as a data-driven decision-making system. Significantly Minsky [34] highlighted the shortcomings of symbolic AI and encouraged a stronger emphasis on data-driven approaches for causal and fuzzy reasoning. The databases of knowledge Ire used in the 1990s and training information to obtain knowledge-based artificial neural networks [35]. Furthermore, in geosciences, perhaps most notably in predictions, information convergence goes back to the 1950s. Indeed, there is an entire discipline named data assimilation, which deals with techniques incorporating mathematical and mechanistic models to enhance forecast accuracy [36-37]. The recent development in research activities indicates that the fusion of data-driven and knowledge-driven methods is becoming progressively crucial in more fields. A recent survey synthesizes this into a modern theory-led data science model, emphasizing the value of enforcing empirical accuracy in ML [38].

The dissertation complements the above work by offering a formal categorization of information representations implemented into ML. I introduce our framework of knowledgeable ML in this portion. I first state our notion of meta-learning, structured prediction along with CEP and then provide our descriptive conception of incorporating them into ML. Selecting and developing an appropriate algorithm to solve multi-objective problems is of utmost importance. To explore efficient solutions and address the related issues from different aspects and handle the resource allocation constraints at different levels, the existing state of the art needs to be studied and discussed. This section provides a detailed overview of resource allocation and load balancing techniques, methods, and algorithms at different dimensions and levels.

2.2. Environmental Health Monitoring and Processing

Detecting and forecasting environmental hazards can better prepare us to mitigate the hazardous effects by improving early warning systems with detected spatial, temporal, and magnitude factors. For example, detecting a healthy residential district based on CO_2 levels or the most convenient time and place with appropriate weather circumstances. Emission levels and Climate Temperature-Humidity Index (THI) events Ire detected from the acquired datasets.

In the detection and management of natural resource pollution, event detection techniques are implemented. For instance, IoT sensors have been used to track outdoor air quality [39]. The health and environmental-related events that individuals will find out about can help in avoiding disease. Since sensor-based event detection was extensively detailed, it has been applied to a wider range of domains. From both environmental monitoring and regulation (e.g., detecting, level of air pollution in a city or climate comfort).

Data about the properties of the event is collected with the help of sensors. Which are usually composed of real-world contextual features (e.g., temperature, carbon dioxide levels, humidity) in addition to Spatio-temporal features since every sensor observation is mapped to a point in time and a specific location. Many studies [40, 41] agree that sensor measurements are known as atomic events (e.g., temperature rise event). Thus, the works concerning sensor data fusion [42] may lead to the complex event.

In [43], the researchers use a crowd-sensing method to identify and track air quality-related activities to detect and monitor air quality-related events in a region with respect to air pollution. Although not entirely confirmed, there is proof that air pollution incidents, in addition to other causes, are linked to the contextual features of air pollution. In [44], the authors focus on indoor air quality because it leads to various illnesses. When accurate knowledge regarding air quality in indoor and outdoor spaces is given, a healthy climate will offer the maximum suitable amount of airflow and maintain healthy and pleasant living conditions.

2.3. Cassini–Huygens Interplanetary Mission Research Scope

Any of NASA's most mind-blowing and the most creative flights is performed by robotic spacecraft that can venture far further than human beings dare. These tasks investigate unique entities in our solar system. More and more interplanetary missions also contained celestial objectives. Most scientists agree that the substance that makes up planets remains unchanged over time and that planets evolved quite early in the creation of the solar system. Planetary research missions such as C-H are used to learn how planetary structures shape, how they shift over time, and where another planets life can be contained. There are several space organizations, such as NASA, studying our solar system and far more of planetary discovery, Cassini is among the most innovative attempts ever pursued. The ESA, the Italian Space Agency (ISA), and NASA banded together as players in the league to accomplish the task of making this project succeed. And, the most exciting element, a sophisticated robotic spacecraft that's been traveling across space on a quest to discover Saturn and its complicated structure of rings and moons. Cassini took with it a probe named Huygens. The spacecraft was outfitted with an assortment of equipment that could take precise measurements and include comprehensive images in different atmospheric environments and light spectra.

The Cassini missions have provided unprecedented information about the solar system. Since its rollout in 1997, Cassini has traveled 4.9 billion miles and has accomplished 294 Saturn orbits. This, in essence, has produced a massive volume of research – more than 4 thousand scientific articles have been written since the missions began in several fields such as surface temperature, climate, atmospheric data. The data obtained from the Cassini mission has been enormously useful to potential science, and the cessation of the Cassini mission is the culmination of an unprecedented era of our space research missions. The project has opened up fresh mysteries that researchers would now have to explore without a spaceship. The probe, designed by ESA, was released on 25 December 2004, and hauled to the surface of Saturn's biggest moon, Titan, in January 2005. Huygens provided stunning images and other experimental observations after the plunge into Titan's hazy atmosphere. The HP submitted its data and measurements to the Cassini spacecraft, which then sent it all the way back to Earth.

The scope of implementing general AI techniques have been introduced in several domains. In [45], Girimonte from the ESA surveys many research fields of AI for space applications, particularly: distributed AI (comprising swarms); big data analysis; and decisions on spacecraft device configuration. In a general context, growing quantities of applications need continuous processing of streaming sensed data at various sites, at different times and speeds, to gain added value in their utility domains. Real-time computing is also the subject of raw data processing.

The mission comprises two parts: the first one is the CO, and it aims to examine Saturn and its surrounding rings and the electromagnetic spectrum of Saturn moons. The second one is the Huygens probe, which was sent to the atmosphere of Titan.

This Remote Sensing (RS) method will show the characteristics of the planet Saturn and its satellites. The inspection process of Saturn satellites' formation circumstances could be the paramount factor to comprehend the formation of the planet Saturn and the rings around it. Paula S. Morgan [46] introduced the challenges that the mission of C-H had faced starting with preserving the domestic health and the operability of spacecraft instruments and devices, dealing with solar radiation and heating, cold of outer distance space, the presence of fault tolerance, power saving, in addition to the surrounding environment such as the delay that took place between Earth issued commands and the mission spacecraft especially when it was brought closer to Saturn planet.

While Nass et al. [47] investigate the planetary cartography as it offers a base for orbital planning and observation and expedites mission procedures, it also produces scientific results per prosperous mission finishing by converting data into maps archives to offer a backbone for scientific research in the future. Laura et al. [48] proposed an implementation structure for evolving planetary spatial data infrastructures associated with ameliorated spatial data administration, detection, and access. This study aims to deduce a perspective for consolidated infrastructure for both the existing research operation and the future endeavors of data gathering.

2.4. Meta-Learning Approach

Current ML models usually are manually built from the ground up for a given mission. There have been great achievements in DL-based methods in different fields. Meta-learning is an alternate paradigm where a ML model gathers knowledge over several previous encounters – sometimes spanning the distribution of similar tasks – and uses this expertise to enhance its predicted learning output. A useful feature about this 'learning-to-learn' approach is the data and compute performance that can be accomplished. The study on this subject is in line with how learning functions in humans, where learning methods improve over both the short and long periods of our lives. DL demonstrated the importance of joint feature models and relations across features. Meta-learning in neural networks may be seen as attempting to include the next phase in the convergence of common elements, templates, and algorithm learning.

Meta-learning is initially presented in [49] and [50]. ML approaches must master new activities more efficiently by exploiting prior interactions. It is a transfer learning extension and is one of the multi-task learning algorithms. Model-based Meta-learning relies on a model and no conditional probabilistic approach to be the perfect fit for a fast learning model. It changes the hyper-parameters for only a few samples. Updating their hyper-parameters is achieved either by internal architecture or by external meta-learner. However, its ability as a catalyst for the development of the new DL industry's frontier has contributed to an acceleration of recent science. In fact, meta-learning can relieve several of the key critiques of modern DL, for example. Improving data quality by moving information. Meta-learning has successfully been implemented in multi-task situations where task-agnostic information is derived from a set of tasks and used to enhance the newly learned tasks from that context; in single-task cases where a single challenge is consistently solved and strengthened over several episodes.

Many views on meta-learning can be reported in the literature, partially because different peoples use the word differently. Meta-learning is quite generally known as learning to learn and relates to the method of refining learning algorithms over many learning cycles. On the other side, traditional ML increases predictive performance over various instances of data. Meta-learning examines how a learner can boost their learning performance; via practice, the aim is to consider how learning may become adaptive based on the domain or mission under investigation.

The learning mechanisms operate by adjusting to a given context, eliminating the likelihood of placing a partial ordering or prejudice on the collection of potential theories that describe the definition. Meta-learning varies from basic-learning in the sense of the adaptation level: meta-learning experiments about how to dynamically select the correct bias rather than basic-learning where the inclination is set a fortiori or user-parameterized. Experience is best defined as information acquired by knowledge. Analysis of various tasks; the concept is not restricted to improving the theory by providing instances that are part of a particular process. Thus, meta-learning supports the need for the learner's continual adaptation at varying stages of abstraction.

The model-based Meta-learning concept has a neural network that communicates with sequential neural networks to speed up the learning process. In other terms, each mark attempts to learn a model. In other terms, the algorithms of this model attempt to train a recurrent model like the work presented [51], which suggested LSTM. Hochreiter and Schmidhuber [52] first suggested the LSTM theory in 1997. Model-based algorithms sequentially take the data collection and evaluate instances.

Meta-learning is the science of continuously studying how various ML methods work on a broad variety of learning tasks and ultimately learning new tasks quicker than otherwise feasible thanks to meta-data. Most specifically, this involves utilizing ML models that learn how to better integrate the predictions from the various ML methods in the area of ensembles. Nonetheless, manual model selecting and tuning can often be done by a professional on a ML venture and automate this method. It includes learning through several learning processes, such as grouping, regression, and clustering, where the meta-learning model learns the process of how to learn.

2.5. Deep learning-Based Approach for Detection

DL algorithms are increasingly used for remote-sensing research, particularly in the last decade. DL has now been implemented in automated change detection systems and has been productive, which is why it was started. Techniques used in change detection analyze different elements of the observation method, primarily, the systematic compilation, processing, and evaluation of high-fidelity detailed, quantitative details (i.e., data). Extreme weather conditions such as drought, flooding, storms, and heat waves, are no longer uncommon or are more common. At the same time, those events have also become a new problem for researchers and demand for creating more efficient automatic change detection methods.

Hypothesizing that such events may be observed remotely by particular potential technology, deep arrival learning has been implemented to detect changes via RS. Change detection is either the operation of quantifying a change over a span of two distinct stages or otherwise is the study of evaluating whether a change has happened. There are several common implementations of shift detection, including text analysis, face detection, etc.... This change agent appropriately adopts change tracking for deforestation control, hazard evaluation, and changing crop monitoring. Often, it is also used to track the impact of climate changes, even though these results normally arise as amounts of greenhouse gases in the environment are elevated, and only partly account for climate change.

Essential attributes of the planet Saturn and Cassini's mission aims Ire integrated to provide an extent elasticity regarding selecting the science phase trajectory. In the work of [53], an approach is utilized to specify the Rev-15 non-targeted Tethys flyby altitude, impelled via the navigational demands and operational restrictions, besides too many carried out trajectory modifications to minimize the gross Δv costs. Paper [54] presents the latest scientific highlights regarding the orbiter Cassini mission discoveries remodeling and principally modifying our understanding of this one of a kind planetary framework. In the last part of 2016, one of the Titan close flybys modified Cassini's trajectory forming a series of twenty rings forming remarkable orbits. These orbits comprise adjacent flybys of tiny moons.

Paper [55] conducted an analysis of Cassini's trajectory comprising the 1st and the 2nd Titan encounters and portraying orbit determination through a dynamic approach and estimating the parameters related to depicting the final trajectory. [56] Surveyed the trends of AI in spacecraft control and guidance dynamics and concentrated on the evolutionary streamline and DL as it is the key for future systematic investigation in the space field. This is done by incorporating AI and automated reasoning to control the navigation and RS refinement of the outer space mission trajectories. In paper [57], Support Vector Machine (SVM) is utilized to identify trajectories accompanied by various movements among the distinctive trajectory modality, such as deviating events.

Up to recently, prior researches in aerospace that include massive data sets Ire imposed to utilize techniques that are less eligible for modeling impermanent or temporal data. LSTM is an artificial RNNs that appoints a great hop to aptly processing past events information and predicting the future. This type of neural network includes a weighted self-loop constrained with a circumstance that permits it to forget former information besides stockpiling it. The ingrained features of LSTM offer a typical candidate for extreme events detection, including any stream of data and time series. LSTMs are eligible to detect the interconnection among previous and current data, also appointing that connection in the mode of memorized or learned weights [58]. The trajectory prediction approach, termed as a grey dynamic filter, which merges dynamic measurement theory and the theory of grey system is suggested according to [59], an emulation of symmetric/asymmetric accelerated motion carried out. One of the research papers introduces a trajectory prediction approach depending on the induced information assembling factor, intending to recognize the delicate spacecraft trajectory prediction with interlocking arcs handed over by various equipment. It proposes the scope of induced harmonic median operator [60]. In [61], GRU periodic neural network algorithm is provided for actual time trajectory prediction, where its parameters are acquired via batch processing as an initial phase, then the trained input for trajectory prediction. In [62], a model-based reinforcement learning is put forward to execute almost quintessential reconfiguration in establishing flying spacecraft. Along with two other algorithms, the LSTM layer network and inverse reinforcement learning are exploited to remodel and predict future trajectories to acquire collision-free maneuvers. These merits have inspired us to utilize the LSTM networks where the LSTM approach fits our research area.

2.6. Remote Sensing in the Field of CEP

It is important to produce, compile, and communicate knowledge regarding IoT systems. Sensors are connected to different objects to capture their primary functions and positions, and data is transmitted across things using sensor network technology. Technologies that can efficiently process or interpret big data from a sensor network would be necessary to the IoT.

Literature inspection and detailed analysis uncover wide exploitation of sensory data in varied fields spanning from environmental conditions, healthcare applications, industrial to civilian and military implementation, and social behavior recognizing, that are all founded on tracing and analysis of information [63]. In [64], four classifiers Ire evolved, which can be exploited on board the spaceship to pinpoint high primacy data to be sent to Earth, to enlarge the bandwidth utilization of bounded downlink, these classifiers used to recognize events on the cryosphere by hyperspectral imaging. In [65] was introduced and appraised communication methods that could impressively implement CED along with distributed event provenance. The authors of [66] proposed a method for determining whether and how the evaluation process must be reinforced. This approach is counting on a few sets of restrictions to be accomplished via the observed values, delineated to get improved evaluation process is ensured if any predefined principles are breached. The presented method is intended to obviate false positives regarding the most advantageous resolution.

Authors of [67] depict a pattern-based approach querying methods related to remotely sensed data networks, scheme-based techniques to data gathering Ire considered to acquire more productivity. Additionally, they debated dependability-based outcomes and contemplate the reliance among the sensors of network readings. Authors of [68] intend their work to concentrate on the observation of abnormal events in an environment where complex activities are accomplished, and potential abnormal situation differs in various phases, in the given model the abnormal situation among any phase could be converted into event modality termed as abnormal event patterns. The contexts within various times measured by sensors, a state transition is exploited to pattern each phase to detect the regular transition interval at the starting and end of every phase to find an abnormal situation.

Another paper aims to put forward an approach to increase the realization regarding incidents, which could be characterized as events. They adopted an anomaly detection technique depending on the rapid harmonic analysis method and decision-making regulations [69]. In [70] are presented CEP techniques that require a long time to accomplish their tasks, as they do not take into account resemblance and operators redundancy, that what Bok, Kyoungsoo et al. mentioned and put forward in their work an approach that contemplates resemblance and redundancy of operator for sensors data streaming. The focus of work [71] is to provide a framework concerning vehicle interaction. In contrast, uncertainty occupies a considerable amount of their proposed technique as no methodical procedure can completely depict the complex event scenario. Markov logic network is utilized among the terrestrial domain in which dynamic characteristics and relevance between vehicles are grasped via several sources and sensors. Computations to address the concept of complex events within big streaming of data have proliferated remarkably. Also, consummation time is overdue because events could not be processed in a prescribed interval of time. Consequently, research on mitigation of the aggregate computational encumbrance is required and must be included in a situation of events that are primitive, which leads to having complex events that possess redundant and resembling operations.

Feature extraction is considered a decisive aspect in pattern modeling and an essential role in the RS field, as it simplifies the posterior data handling, representation, and classification.

Features could be commonly ranged from bottom to top scale features, even though there is no apparent separation between them [72]. An essential part of the event comprehension is to perceive what triggered it and at which time it is taking place [73]. Observation of complex events illustrating ensnares can decide on the continuing data if the progressing information stream can be coordinated into the available delineation and how it influences the comprehensive occasions' delineation. There is an expanding need for data systems to handle tireless data streams and respond to specific circumstances. CEP incorporates different information sources to identify and address critical complex events among extraordinary events stream depending on unique modalities. A massive volume of events is vague; the outline of event processing imposes the expediency to clear out the indecision [74]. Cognitive reasoning and computing are an up-growing scope of computing suitable to conquer the potential issues that will show up in CEP frameworks [75]. In any case of their singularity, complex frameworks reiterate and generate what could be a predominant cause for logical realization: the quandary of creating a model that can distinguish fundamental viewpoint [76]. So ready to deduce that constructive modeling might be characterized as a field of computers that deals with emulated human troublesome or complex generate mental preparing and arrangement finding inside a computerized worldview. Constructive modeling investigates and is coordinated toward the theoretical scholarly concept and industry category. Front line exploitation of constructive modeling is the generation of constructive machines, which may be portrayed as artificial insights programs that limit human cognition's limit domains.

Remarkable efforts have been dedicated to the aim of detecting complex events and conducting reasoning. Models of this kind are as often as possible carried out as a generation system with a flexible implies that allow the capacity to come over a broad span of plans up to capable accomplishment indeed with complex errands. Schoppek offered a rigorous reasoning model that was qualified to assess and direct a minor dynamic system via reliably relying on linear system equations [77]. The demonstration contained a clear cerebral outline of the technical system and thought procedures to secure input values. The embraced method is satisfactorily comprehensive to organize any simple framework. Consequent considers how these frameworks' approaches may be extended to generalization execution inside complex real essential timing correlation that incorporates choice- forming, such as controlling a jet plane [78].

In planning the errands of actual-time dominion, the noteworthiness ordinarily counts on mimicking the time way of monitoring prepare, and traditional mistakes [79] presented an event scoring algorithm to detect evolution correlations. This algorithm exploits the timestamp, temporal contiguity, content resemblance to display the event evolution interconnections. A plan-based approach [80] proposed a plan-based method for exchanging information related to CED over distributed sources, providing a cost-based multi-step identification scheme depending on the temporal constraints and event frequency statistics ingredient events.

J. Yang et al., the authors made an imperative stride about suggesting a CEP by counting on reasoning principles and the scope of computing, in the role of that they overviewed the extant methods among three aspects included in semantic, iterative, and intelligently [81]. Storrs, K.R., and Kriegeskorte, N. have tried reasoning speculations by utilizing profound learning instruments to assess its helpful and incipient behaviors. In arrange to utilize profound learning to enlarge the prepared speculation show to be qualified to perform complex errands. In [82], the authors introduce appropriate schemas and techniques used in reasoning modeling, reasoning with good sense, and sound judgment in practical matters.

Moreover, defiance and significant research questions are presented, e.g., developing a complex computational paradigm that can be a contestant with humans' reasoning on trouble that needs general sense or significance. In the role of researchers in [83], they illustrate the leverage of integrating reasoning with ML and neural-symbolic computing via delineating the significant features of the schema and representing the reasoning that allowing building an interpretable AI framework which could lead the way for the growingly eminent necessity for the explainable and trustworthy system. The work of [84] addressed the significant challenges within the field of ML and reasoning products and provide stimulations for additional development, especially in the scope of empowering reasoning competence, just like cognition and perception, which could lead to additional dependability, robustness, and enhanced performance, their work suggests a top-level reasoning schema, that is targeting conceptual prototypes of reasoning scopes.

[85] This paper presents a performance model and an ontology approach to discover or identify the presence of complex events for the actual time during which a process or event occurs in the system. These previously mentioned works have incurred and stimulated us to utilize the intelligent mechanism via stacked bidirectional LSTM network layers to identify a CKE.

2.7. Structured Prediction in the Scope of Reasoning

In recent years I have seen a significant volume of progress and success from deep neural networks. The underlying explanation for getting Neurons is to acquire resemblance trends from data as means to predict and conclude. However, it is the practical skill of logic that enables both theoretical and functional issues to be solved. On the other hand, conventional symbolic reasoning approaches are effective at allowing a rational conclusion of a statement. Also, though taking into consideration that "different situations may require different rules", the automatic reasoning components are mostly hard-coded rule-based reasoners, restricting their generalization capacity to different activities. The logic and generalization skills are critical for recommender tasks that require data that is used to forecast. Categorizing and predicting consumers based on their previous interactions means that the model will create the correct forecast. It also lets the model generalize based on unpredictable inputs in the future to make reliable predictions.

Structured prediction attempts to learn a predictive model that incorporates characteristics that are present at the input. Structured prediction is particularly relevant in many daily scenarios. In spatially structured prediction, it seeks to learn a predictive model that takes spatial structure into account. Data analysis and ML are becoming increasingly common in such scenarios, yet segmentation is perhaps the most important and necessary application. It is necessary to learn a model that can conduct probabilistic inference and render different predictions in organized performance prediction. It's because I're not just modeling a lot-to-one thing task as in classification activities. However, I may have to model projecting from a single input to a variety of potential outputs.

The topic of prediction includes a number of various ML activities. Structured prediction is basically a representation issue that considers both the exclusionary interactions among x and y and the best combinations of y that can be produced from x. The reality that prediction of organized language pairs can be mastered utilizing predictive methods, breadth of comprehension, and other forms of algorithms such as DL, is an unsurprising realization considering the current understanding in AI. Structured prediction is a ML approach that offers a coherent treatment for coping with structured performance variables. The frameworks assisted in designing more sophisticated models. There is a need for more effective models because of science society's view that a broad range of complex scope can only be grasped by feature vectors and constraints. There are some essential things to address when looking at computer programs in the area of computer-assisted prediction: the description of the world; the process by which the model portrays the world; if the technique used for training the model is a controlled or unsupervised method; and finally, the application in which the training is occurring.

Structured predictive analytics identify predictive models for leveraging trends contained in historical and transactional data and detecting opportunities. Models capture associations between various variables for evaluating, or theoretically correlated with a complex collection of parameters, influencing applicant transaction decision-making. Predictive analytics is currently used in many sectors: financial services, banking, transportation, hospitality, travel, healthcare, pharmaceutical, etc. Predictive analytical approaches founded on complex event data will forecast the tracked framework's characteristics based on previously monitored incidents. In general, a prediction mechanism consists of four steps: (1) gathering and pre-processing raw data; (2) converting pre-processed data into a type that can be efficiently managed to utilize the (selected) ML approach; (3) building a learning model using transformed data; (4) reporting predictions using the previously generated learning model. Using recent data focused on the learning model learned for previously monitored events will forecast future events.

Several available research efforts carry out approaches reasoning throughout a supervised process of the pattern of structured learning and all lead to a common purpose. Such techniques could be generally split into that one’s mitigate the effectively conveying influences along with the space separating the output of the variables [86]. In [87] they utilized the information hypothetic regulation for obtaining a generalization frontier that relies on the mutual relationship or connection among the class functions accompanied by the input and output dependence of the adopted learning model. Several tools and techniques Ire developed and utilized in many space missions via consolidated approaches accompanied by data mining techniques [88], [89].

2.8. IoT as a Source of Innovation

If the exponential growth of IoT sensors proceeds, I will have the potential to know everything, wherever, anywhere, all measurable things. Already many IoT-based mechanisms sustain homeostasis efficiently, similar to many dynamic physiological processes. Absolute autonomy of these closed-loop homeostatic systems is likely to become a commodity operation.

The role of innovation in these systems is extracted from the information of process optimization based on a modern understanding of involving processes (including science and new sensing ability (including technology), which is one of the core elements in this innovation. Autonomous systems based on prevalent science and technology are designed. Any time of scientific and technical stability makes the positioning of analytics closer to the data to increase, "meaning signal to control centers and leave or discard noise closer to the local sensors. Whenever new research or technology arises, though, the data needs to be more centrally filtered and processed using DL software to re-adjust the entire self-sufficient working system based on a more in-depth understanding. Each autonomous service may have various components of different times to decide what signal and noise are. This causes many accordions that open up new signals (formerly called noise or silence) and close as new signals are produced. Anomaly detection of outlying occurrences would be another reason for opening the accordion. This is an evolving learning and design process.

Smart space represents a transparent, ubiquitous area that forms one of the primary sources of big data. It facilitates the provision of critical resources through data and environmental information acquisition. One objective of smart space is to attain an omnipresent atmosphere of embedded sensors and computers to optimize human activities and decision-making through the close partnership of omnipresent digital technology and Internet services. Developing service construction for end-user apps and IoT-related computing environments includes smart space. However, it is crucial to recognize data quality as part of the critical criteria that guarantee smart spaces' established goals. The urge to enhance smart spaces service development continues to rise as sensors' cost remains reasonably low, providing an accessible, pervasive computing climate. Sensor readings create a high volume of data provided in this environment.

IoT data is generated in many areas, protocols, and computers. IoT attracted smart office construction, apartments, and neighborhoods. In the IoT model, items may be person and world connected to sensors or small-computer-controlled computers. The analytic helps extract pertinent knowledge, grasp patterns detected, and promote recommendations. Considering these innovations, the scalability of data processing and storage is assured. However, terms such as CEP are introduced into this sense to facilitate the processing of various categories of events, identify similarities within them and use rules for this, representing market criteria found in each enterprise's context. Using multi-device analytics enables data aggregation through various device hierarchy layers and allows users to post custom requests on aggregated data.

Predictive analytics (e.g., classification, estimation of the next attribute, identification of anomalies) allows data selection and advanced processing using ML techniques. ML learns a sample data underlining feature. Initially, most ML algorithms are created, focusing on batched data analytics. Many ML analysis issues include fitting models to the data as data is collected and modifying models over time. Using advanced analytics with integrated AI and ML capabilities, evaluate structured and unstructured data sources, including the sensory measurements and image recognition.

IoT is indeed the umbrella word for a wide variety of underlying technologies and utilities that are reliant on usage cases and, in turn, are part of a broader technology ecosystem that involves similar technologies such as artificial intelligence, next-generation encryption, predictive analytics, big data, multiple connectivity/communication technologies, cloud computing, digital twin emulation, enhanced data.

Chapter 3: Proposed Methodology

The reason for conducting our research studies is its originality as it has not been carried out by any other researcher elsewhere, also I introduced the multilevel concept of CEP. This chapter outlines the experimental setup used to test the research hypothesis. Sensory data are explained, and their dependencies are identified with each other. The chapter also describes the modules produced in this work. The chapter realizes the methodology to satisfy the theories. It discusses the dissertation work methodology. The chapter presents and describes numerous phases in the execution of the methodology aspect. It illuminates the preparation of training data and shows the neural network's design and other technical information. The dissertation provides the CKE algorithm, Meta-Learner LSTM algorithm, and a structured prediction approach for multi-label classification that moves past the binary relevant method by studying a classifier for each potential label and only makes predictions separately. The proposed approaches cast the learning as a structured prediction, one with losses adequately designed for the task: the F1 and Matthews correlation coefficient. Subsequently, it illustrates a real-world dataset of the merits of the proposed approach.

CEP is a framework to extract meaningful information from data streams. Two streams sometimes define the same observable reality in two distinct forms. I recognize the sound of thunder first. And I'll notice a drop of water dropping on our skin. I pair these two occurrences with our experience of local weather to assume that the sky is beginning to rain. CEP does the same thing. CEP takes input from different outlets, interpreting it into a domain-specific context and understanding the significance in terms of high-level definitions and complex events. CED is evolving as a core feature for many application areas, such as detection scope, sensor-based behavior & phenomenon monitoring, and network monitoring. CEP is a sweeping statement of conventional stream processing. Conventional stream processing is dealing with the detection of low-level data patterns. CEP is providing a lot more, using causality models and logical hierarchies, CEP may draw high-level inferences. The usage of logical hierarchies is one of the defining features of CEP. I all realize that the actual events arrive at varying levels or degrees of event processing logic (abstraction). At one level, I can consider air quality or pollution level. At a lower level, I can consider the actions of data gathering. Within the scientific and business sector, CEP may establish high-level assumptions regarding complex events. When interacting with more than one level at once, it will be challenging to keep track of a single time-ordered stream of events. CEPs are characterized by the usage of causal interactions, rather than a cause and effect relationship. If I'm looking for a method of addressing a particular trend, I anticipate an event to occur. By employing the CEP application, I can conveniently flag a combination of events as complex. However, it is necessary to note that the data measurement does not necessarily arrive at the same predicted time series. The main advantage of CEP is that pattern may be caused by a mixture of events taking place at various periods and in different situations.

CEP helps businesses to build useful insights out of raw data and information knowledge. CEP may arrange data into a higher-level of abstraction (event processing logic), considering various time periods, backgrounds, and causal relationships. Using CEP, businesses will react in a clear and rule-based manner to opportunities and risks. As data are more and more available, it makes CEP crucial for event-driven architectures. Almost all prediction methods depend on the detection of complex trends in vast volumes of data from different sources, rendering CEP a core part of the predictive analytics context. CEP profoundly affects integrating knowledge from diverse channels by gathering IoT sensor feeds for meaningful tracking, analytics, and system integration. A smart building will gather the data that comes with different sensors, including light and heating regulation, as Ill as details from sensors that tracks temperature, date and time, and so on, and will then predict the actual actions of tenants, proportioning illumination, heating, and so on. If I consider an event is any group of results, including outcomes, from a random setting. For a given event E, $0 \leq$ probability (E) ≤ 1. I have made the CEP on multi-level processing, whereas the first level is based on data analysis, while the second level is information analysis (in our case, was OR) probability (E1 OR E2 = E1 ∪ E2). Venn diagrams are helpful for keeping track of how events are associated. Here, circles reflect a particular event. Figure 3.1 shows a Venn diagram for two events OR association. The study of big data aims to provide a theoretical basis analysis of data, which gives the context to acquire a piece of information.

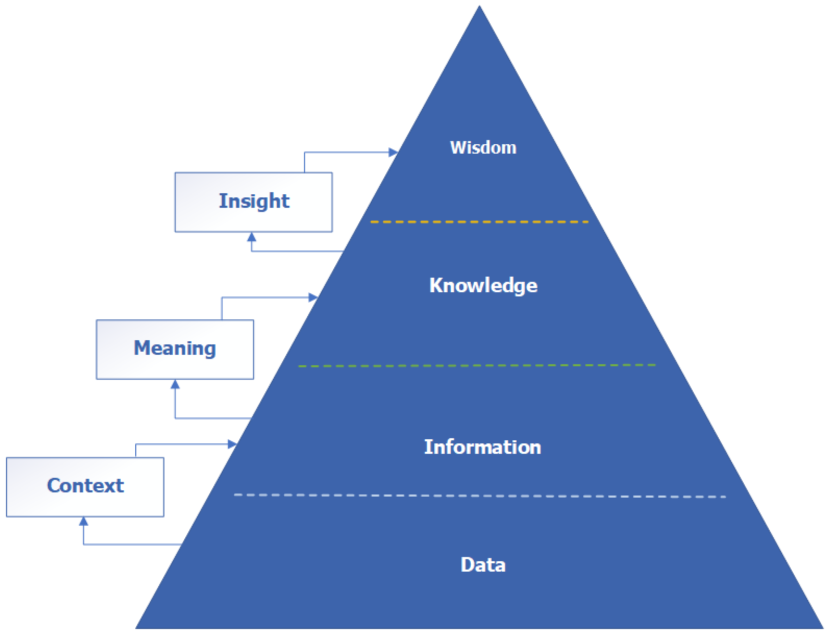


Figure 3. 1: Venn diagram of data processing levels

This information has the meaning to get the knowledge that will provide the needed insight to have a pearl of wisdom. This approach is a more coherent model based on data, information, experience, knowledge, and wisdom. Typically, data and knowledge are interchangeable in common language. Data is the product of reasonably precise observation. Data contains factual truth, and there is no requirement for relationships to occur with other components. It does not express anything and does not hold any significance if you take each data separately. Data is what the senses can interpret or count or perceive with a device such as sensors, but once you bring it into context, it is meaningless. Data becomes data only when contextualization (in fact), classification, encoding, correction, and synthesis position it in perspective. By means of figures, Information has greater importance than the data. It's the option of data that one can determine and behave and obey then conclusions. These findings are referred to as "information" without being linked to any real subject matter or thing. Knowledge is a mixture of evidence and intelligence that brings professional opinion, knowledge, and expertise to building a critical tool that can be utilized to assist decision-making. Wisdom is intangible, immaterial. It is the decision, the willingness to add meaning. Wisdom moves beyond information and wisdom principles and embraces the assimilation and translation of these into human interactions. Wisdom embraces knowledge and enables one to choose better.

3.1. A Generic Environmental Events Detection Approach

I'm modeling the events as 3D+ spaces (having at least three dimensions, such as spatial and temporal). For each sensor, one may determine qualitative events dependent on sensor measurements (e.g., temperature, humidity) and different degrees of granularity for each merit (e.g., day-month-year, hour: minutes: seconds for the period.

3.1.1. 3D Framework to Evaluate Healthy Residential District Based on Sensory Data

Spatial representation of CO2 emission level provides a visualization environment that supports and combines the manipulation analysis and interpretation of the complex data to estimate and monitor the CO2 emission level and evaluate convenient, healthy residential district based on environmental sensory data sets. I'm trying to uncover three concepts associated with air pollution: the first one is the public ignorance regarding the air quality, the influence of that pollution on their health, and the difficulty of acquiring information associated with air pollution. The method provides visual analytics of multi-dimensional spatial features of an extracted CO2 emission levels of the 3D Road network dataset, which is a 3D road network dataset with quite precise elevation information this data set is utilized in eco-routing and in the scope of fuel/Co2- emission estimation. This data set was initiated by combining elevation information to a 2-dimensions road network located in North Jutland, Denmark, the values of elevation where acquired from a publicly obtainable enormous laser scan sensor point data Cloud for Denmark. The EcoMark [90] scope for assessing a paradigm of vehicular environmental (pollution) influence clarifies how utilizing a precise 3D approach produces a more improved prediction of fuel consumption and greenhouse gas level of emissions generated from vehicle transportation. Our research will use the "3D Road Network (North Jutland, Denmark) Data Set". This data set covers a total scanned region of (185 x 135 km2). The data record structure downloadable from the source is in table 3.1. It can be observed that the accuracy of the altitude is 1*exp-13 because of the special, laser-based scanning method.

Table 3. 1: Structure of the captured data set

Sample#	CO_2 level	X	Y	Z
1	144552912	9.3498486	56.7408757	17.0527715677876
2	144552912	9.3501884	56.7406785	17.6148402443890
..	…	…	…	...
434874	93323209	9.9434512	57.4962700	24.6352847839592

The accuracy of the longitude and latitude is 1*exp-7, which conforms to the GPS characteristics. The map has been formed as a shape of arrays with a relative size of 10%x10% of the regions, so that the first region is symbolized as R1,1, while the last region is represented as R10,10, consequently. I'm going to specify the healthy or unhealthy region residential districts based on the conducted analysis. The environment quality is evaluated by estimating districts based on the CO2 level of the analyzed territory. Outlying regions Ire found based on the environmental sensory dataset, being an important environmental protection task and providing a healthy lifestyle for humans in that peninsula.

3.1.2. RS as a Tool to Detect Climate Comfort

Tour agencies and tourists could exploit such indexes to specify the ideal time to start their vacation or plan a trip during a convenient climate. To form up TCI, the amount of precipitation should be considered, as shown in Table 3.2. Precipitation element has allotted 20 % of TCI weight.

Table 3. 2: Precipitation scales variable [91]

Variable rate	*Average monthly precipitation*
5.0	*0.0-14.9 mm*
4.5	*15.0-29.9mm*
4.0	*30.0-44.9 mm*
3.5	*45.0-59.9 mm*
3.0	*60.0-74.9 mm*
2.5	*75.0-89.9 mm*
2.0	*90.0-104.9 mm*
1.5	*105.0-1 19.9 mm*
1.0	*120.0-134.9 mm*
0.5	*135.0-149.9 mm*
0.0	*150.0 mm or more*

The assigning of the proper measure of sunshine for the formula of TCI, as shown in Table 3.3. The sunshine element has allotted 20 % of TCI weight.

Table 3. 3: Sunshine scale variable [91]

Variable rate	*Average monthly hours of sunshine per day*
5.0	*10 hrs or more*
4.5	*9 hrs - 9 hrs 59 min*
4.0	*8 hrs - 8 hrs 59 min*
3.5	*7 hrs - 7 hrs 59 min*
3.0	*6 hrs - 6 hrs 59 min*
2.5	*5 hrs - 5 hrs 59 min*
2.0	*4 hrs - 4 hrs 59 min*
1.5	*3 hrs - 3 hrs 59 min*
1.0	*2 hrs - 2 hrs 59 min*
0.5	*1 hr-1 hr59min*
0.0	*Less than 1 hr*

While assigning the proper measure of wind speeds for the formula of TCI as shown in Table 3.4. The wind speeds element has allotted 10 % of TCI weight.

Table 3. 4: Wind speeds scale variable [91]

Wind speed (km / h)	*Trade wind system*
<2.88	*2.0*
2.88-5.75	*2.5*
5.76-9.03	*3.0*
9.04-12.23	*4.0*
12.24-1 9.79	*5.0*
19.80-24.29	*4.0*
24.30-28.79	*3.0*
28.80-38.52	*2.0*
>38.52	*0*

The incoming is an illustration of the "Bullet" pattern, which is the most likely recognized and utilized indices in the tourism field which is the (TCI), The TCI is the most ubiquitous climate index promoted particularly for tourism, the limitations of meteorological data has been minimized as many climatic factors were grouped into the TCI to be five indices instead of seven, as it appears in Table 3.5. which also include the impact on TCI and the avoirdupois of each element. Computing the TCI was first proposed by Mieczkowski [91]) as shown in the following formula:

$$TCI = 8 \cdot CID + 2 \cdot CIA + 4 \cdot R + 4 \cdot S + 2 \cdot W \tag{3.1}$$

The score of Daytime comfort index (CID) has been specified by utilizing two parameters comprising minimum relative humidity and the monthly maximum dry temperature, while the score of Daily time comfort index (CIA) has been determined by mean (μ) relative humidity and μ dry temperature, R represents rain, S symbolize for sunshine and W for wind speed.

Table 3. 5: Elements of (TCI) [91]

Symbols	*Sub-index*	*Climatic elements on monthly basis*	*Impact on TCI*
CID (40%)	Daytime comfort	Maximum Temperature per day and daily respective humidity	Thermal comfort over max tourist vitality
CIA (10%)	Daily comfort	Temperature rate per day and daily respective humidity	Thermal comfort during 1 day
P (20%)	Precipitation	Total precipitation	Negative effect of precipitation
S (20%)	Sunshine	Total hours of sunshine	Impact of the volume of sunshine
W (10%)	Wind	μ wind speed	Impact on μ wind speed

TCI scale has been categorized into 10 classifications that characterize climatic conditions. The conditions of Human comfort are detected by other indices depending on a collection of several meteorological parameters. Measurements units used in this research paper include several parameters such as degrees Celsius (°C) for temperature, mm(millimeter) for precipitation, wind speed (knots). The process of specifying the tourism climate index will include the following steps: the first step includes the metrology extraction, then calculates the index of comfort in day time depending on monthly maximum dry temperature and the lowest weather moister (CID). The third step is to compute the comfort tourism climate index depending on the influential temperature index and the average moisture.

3.2. Event Detection by Structured Prediction Based on Revealing Event Complexity

CEP is a modern and greater inclusion that enables data analysis of stream events. CEP's principal aim is to monitor the dynamic event trends of low-level and atomic events such as sensor data. Determining rule patterns for matching these basic events based on temporal, semantic, or spatial associations is the core challenge of CEP systems. After maturity, Big Data Systems and IoT technologies require sophisticated AI approaches to automation in the CEP domain. CEP is a meta-framework of techniques, e.g., filtering events, matching event patterns, timing analysis, a hierarchical abstraction of events, creation of complex events, the definition of event hierarchies) for processing event flows in real-time and abstracting humanly understandable and actionable knowledge from such event flows. By comparison, AI has experienced colossal development in its potential definitions from its initial inception. AI will also use CEP systems or event streaming platforms to process incoming events and feed them into neural networks. The CEP stream processing logic preprocesses input data chronologically preceding other smart components and allowing them to execute tasks they may otherwise not have been able to perform.

ML provides the ability to identify remotely sensed imagery accurately and efficiently. The benefits of ML include managing high dimensional data and mapping groups with very complicated characteristics. However, applying a machine-learning classification is not easy, and the literature offers contradictory guidance on specific main topics. Accordingly, this essay offers a description of ML from an applied viewpoint. It is focused on the relatively mature methods of CEP, which is associated with the identification of complex events focused on domain specialist rules and trends. The meta-learning LSTM and CKE algorithms can better analyze vast volumes of data within a small-time interval and supervised learning via structured ML prediction.

By concept, an event is something that occurs or is perceived to happen [92]. Events can occur in the actual world, for example, aircraft landed or virtually (for example, aircraft landed in an aircraft simulator). Events can physically come from an external database, data sensor, operation, business information systems, etc. [93]. Events are distinguished on the grounds of their complexity: an event may take place to be simple or complicated. A dynamic case is abstract simple, or complex incidents; e.g., aircraft landing is a dynamic case consisting of many basic or complex events: the pilot raises drag, controls crosswind, flare adds. The events may be arranged linearly in event streams or event clouds ordered partly. Events move from event origins or suppliers to event sinks or customers via event networks. An event processing engine serves as a sink for simple events and a generator of complicated events. Usually, events could be judged as a solitary incident that takes place in time. In contrast, a complex event can be seen as a set of circumstances or modalities that encompass a specific coalition significance for the system. Every event is allotted with a type depending on two factors: content and its semantics. Primordial event is simple or has the feature as the non-decomposable, however complex event is pinpointed and drawn out by the CEP framework counting on a specified modality or regulations [94]. CEP intends to deduce meaningful great extent-scale event (complex event) from a series of interconnected minimal level events [95]. Contemporary technologies establish the capability and potency to trace and notice significant events that are taking place in outer space [96]. CED emanated as a neoteric technology that can distinguish complex events via classifying, analyzing, extracting features, and matching events. The major notion on the far side of CEP is pinpointing out an incident or event by examining the reason/affect interconnection to each of the plain events that hold on particular facts or information learned about something. The outcome of the previously mentioned analysis is putting forth an appraisal concerning CED, which facilitates the experts' process in related fields to influence or direct the situation or the course of events to confront difficult issues proactively.

CED's process can be seen as a sophisticated identification of the data pattern, where the term pattern is investigated to recognize a specific event modality. Placement of the rule modality or methodology for matching normal events depending on semantic, provisional, or spatial distribution and relations is the CED framework's primary duty. An extreme event is a category of collective conduct within a complex framework, frequently holds noticeable results. Extreme events take place on a considerable assortment of a complex systematic scheme, an epitome of an extreme event may include surprising packet flow on a network, network jamming, a considerable increase in the number of website hits, or a calamitous state such as an immense level of disintegration produced by the casual collapse of nodes [97].

The event definition has obtained considerable interest among the academic scopes. It is frequently described as abstract ideation [98]. For efficient manipulation of the issue of event detection, an apparent tendency came into sight recently to inspect event-specific reveal within a time frame. Usually, the available techniques detect the event by indicating evidence in a driven model, to which the evidence is observed within a particular task of identifying events. Nevertheless, revealing evidence regarding the event and its complexity upon this method would hold some restrictions, such as the reveal process is carried out in supervised style, to which the data is manually labeled to train task-particular paradigms. Additionally, the evidence revealed with this approach could only be utilized to vindicate pre-detected events. Consequently, research directed to a better ingrained open-ended structured prediction learning and reasoning based on revealing event complexity sounds to be as yet absent. To promote the approaches throughout this tendency, I put forward an unsupervised revealing algorithm that can detect the implied event complexity from a collection of special events. In this research, the complex event is outlined as the potency of special group events frame to represent the event that comes into view in a certain period.

This part handles the schemes selected by the framework for event detection. The steps engaged mainly involve collecting and detecting low-scale and simple events, which may reveal a greater level of complex events. Any new inbound event will be listed inward the framework with a discriminatory event indicator or identifier. The identification of an event is carried out through observing a sequence of actions that are regularly followed. Recognition of low-level events includes revealing simple or plain events, whereas the recognition of high-level events addresses identifying complex events. To reveal a complex event, the methodology initially reveals plain and low-scale complex event depending on a set of explicit or understood regulations and principles governing each event denomination, then the system forwards all of those events to its storing memory, where temporal or even logical factors are utilized after revealing events to realize a higher complex event. For instance, in any given time-series with k time phases, its related weighted Extreme Pattern Score (IPS)score array can be indicated by C. The size of this array is k*k. Every column of the array includes the IPS score for a specific time interval, which is computed by utilizing various series of significant time events. With more elaboration, column y in C holds the IPS scores for a specific time interval (T). The value in column y and the row x will be just like C (x, y). If x < y, then the IPS score for a time interval t, can be calculated depending on a predictive paradigm, which has been trained via time interval that extends from T_{x-s} to T_{x-1}, where s is a prespecified extent of the training screening window. Figure 3.2 gives an overview for the process of special event detection where x represents a special event, W is the window size, and ρ controls the width of the band, the μ of a specific interval that contains an event can be determined by the following formula:

$$W \pm (\rho).(\sigma) \tag{3.2}$$

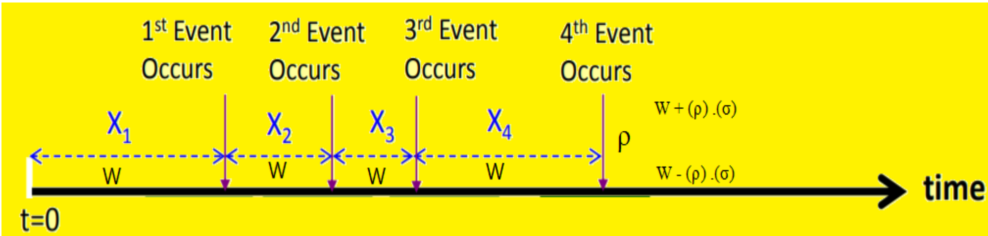


Figure 3. 2: Overview of the special event detection process

Representing and organizing an event within ML is decisive to artificial intelligence. Events are a sort of great significance or value of information representing a machine-readable recognition of structured events [99]. An event depicts an apparent property or can be logically proved in a particular time interval [100]. Event extraction merges cognition and involves several scopes, such as artificial intelligence, computing, information modeling. [101]. Progressively, event extraction has touched other areas like finance and the activities associated with a country's governance, where events are associated with other entities [102]. Despite the conceived utility and vast pertinency of event extraction, various obstacles must be conquered [103]. Regarding the extraction of data-driven events, I have unambiguous singularity between unsupervised and supervised learning techniques. Unsupervised learning is usually utilized to explore data, while supervised learning commonly generates new events, based on the provided labeled examples, which conclude the event features through the training data. Amalgamating unlabeled with labeled data could create enormous ameliorations within the accuracy of learning [101]. This engagement comprises indicating instances of particular kinds of events and their related attributes [104].

Prediction Models

Structured prediction is considered as the backbone of many ML enforcement. Contemplate a setting with a scope of structured prediction of input (a) from the scope (A) is towed to output (n) in the output scope (N). Contemplate a setting with a scope of structured prediction of input (a) from the scope (A) is towed to output (n) in the output scope (N). Moreover, the specified output variable n is a magnitude of binary labels {n1, ..., nk} mapped from N ∈ {0,1}k. The space N might be given via a group of declarative restrictions which could be seen as a shape of identifying framework over N. Reasoning: The labels that exist in N all have a mutual relationship or connection, in which one thing affects or depends on another, which is a favourable circumstance to predict them concurrently. I distinct the prediction along with the whole variables in N by utilizing a scoring-function $g(A, N; W) = W.\theta\ (A, N)$, just as below in equation (3.3):

$$arg\ \max g(A\,, N; W) = \arg\max W.\theta\ (A, N) \tag{3.3}$$

Feature Engineering

Feature engineering can be defined as the process of performing arithmetical transformations or instance of converting of a raw of input data to initiate not existing before features to be utilized among ML model to establish features which are more facilely explicated also boost the innovation by utilizing massive datasets of features, which will lead to improving the power of predictive among the training model. Figure 3.3 represents a proposed ML model concerning feature engineering.

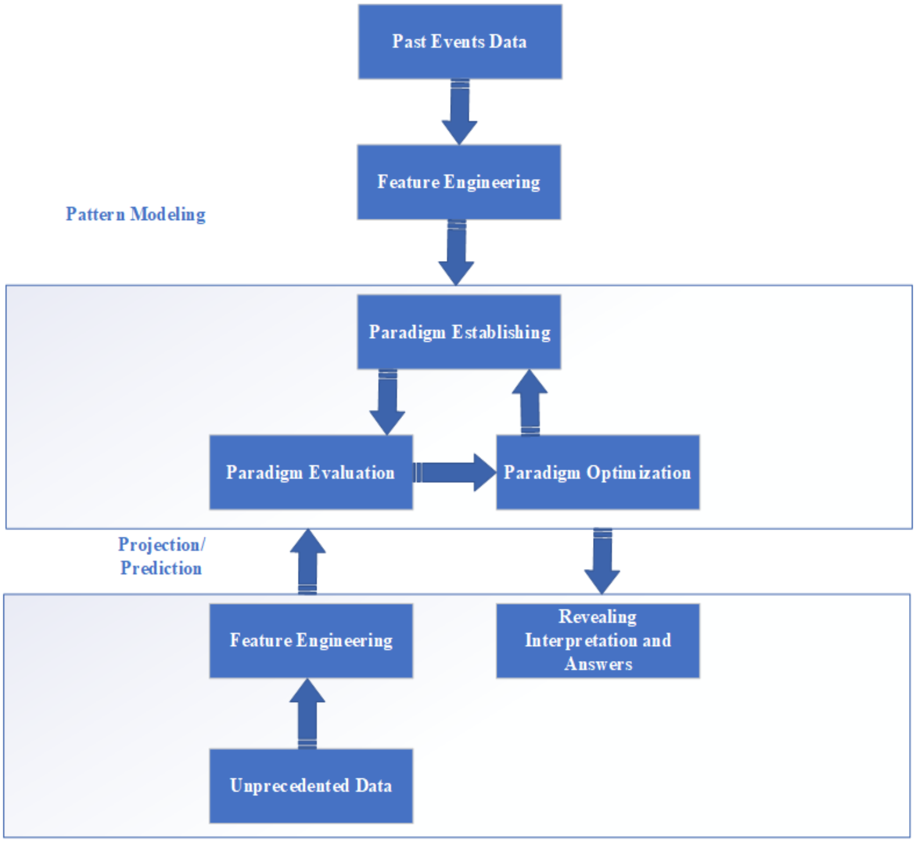


Figure 3. 3: The Process of fitting feature engineering within the ML approach

Also, may defined as the method of creating new functionality to improve the predictive capacity of the model. Engineered features are important since they contain and more important details than the initial features. Feature engineering is always performed first to create new functionality as Ill as the selection of appropriate features. The reliability of the training phase is improved by the engineered and chosen features of the data. They often boost the precision and reliability of the models to predict what is of importance. Often, it is not appropriate to conduct feature engineering or feature selection. The data must be gathered, the algorithm must be chosen, and the experiment's intent decided. Our data processing strategies depend on function engineering now more than ever. Without the data accessible, these algorithms cannot work. ML and data processing function engineering offers a detailed insight into functions engineering, including feature development, extraction, transformation, and collection of features and interpretation of operations.

I should enlarge the training data to raise the related algorithm's preciseness when performing prediction. Feature representation takes a significant involvement in the analysis missions among the expeditious advance within DL techniques [105]. It was found that, the research is near the fundamental issue with better features, reflecting all the data available, and will use it to describe the underlying problem better. Effective features ensure better outcomes, simpler models, and ensures flexibility. I must put forth new data via an identical feature engineering process in an application for the training data. To ensure that the prediction is produced by properly utilizing the exact process used phase of data training.

Applied Methodology

A potent method for identifying variation is utilized to detect if an event has taken place within a particular image, depending on an evaluation conducted on the former and the subsequently captured images in the batch. The existence of adequate veracious data is assessed as an initial phase to detect if the change is due to a special event also to make sure that there is no malfunction in the camera that is taking the images; if these predefined benchmarks are met, then a second phase is carried out to analyze these benchmarks to detect the existence of complex event or events. Pattern categorization is the task of allocating a category label to an event or object. The allocation is counting on criteria and the sampling acquired from the event. The sampling process is made obtainable by the sensory framework. Feature Extraction: provided with a set of characteristics $C = \{e_1 \dots \dots . e_n\}$, the main aim is to extract(map) some characteristic 'C' that increase the learning system potential to categorize patterns. The engagement across the space separating events within the domain of conditional subjunctive ordinarily contains a conditional probability, presuming that an event conditional allocation persists to be steady with particular measures. As an illustration, the scene probability of an event at the time interval($(i + 1)$ relies on scene probability at the time interval (i) besides the data noticed during the time interval $(i + 1)$ among object chain handling. Therefore, the determination of the probability of concatenation scenes can be obtained via the Bayesian rule. Occurrence sequence $S = \{e_1 \dots .. e_i \dots . \dots .. e_t\}$ represents an event, or object that has an act or instance of moving past or through these time intervals according to a particular sequence or pattern, e_i illustrates the occurrence of an event at a time interval (i), its probability is calculated as below:

$$P(sum) = P(e_1 \dots e_i \dots e_t) = P(e_1) \Pi_{i=1}^{t-1} P(e_{i+1} \mid EID_n, e_i) \tag{3.4}$$

where EID_n entitles the id of the event with variable n. Feature extraction is speculated as a pivotal side in the field of pattern molding and image processing, besides an influential part in the RS scope, as it facilitates the subsequent data representation, manipulation, and categorization. Features may generally vary from low to highest rank features, noticing there is no ostensible secession between them [106]. A substantial side of the event perception is to sense what activated it also in which time it is revolving [107]. An event, determined as the incident of interest, could be described as an unpretentious event or complex. The event that takes place at a point within time is known as simple, while the event that happens over a time interval. Complex events merge a single or several events (simple or complex) [108].

Complex events are created via conveniently accumulating events, more accurately beginning with the simple events, where I could append temporal or logical factors to create more complex events. The nominated approach acclimates supervised learning as the method must impart visual significances pertinent to a particular event class by extracting the whole related visual motif and patterns for an event from images. The proposed approach includes constructing a (IPS) array for the related target metadata time series. After that, an alteration score for each timestamp is computed based on the IPS score array; a time series can be defined as a data concatenation of marks gathered over a period of time. Also, they are distinctive to meet the requirements to grasp the variables of the time points dependence. For any given time-series that has k time phases, its related IPS score array can be indicated by C.

The size of this array is $K * K$. Every column of the array includes the IPS score for a specific time interval, which is computed by utilizing various series of significant time events. With more elaboration, column y in C holds the IPS scores for a specific time interval (t). The value in column y and the row x will be just like C (x, y). If x < y, then the IPS score for a time interval (t) can be calculated depending on a predictive paradigm, which has been trained via time interval that extends from px-s to px-1, where s is a prespecified extent of the training screening window. The variation score for every interval of time is obtained via the IPS array. In connection with any time interval (t) and event-detection parameter (e), I designate the classification and labeling-array $L_t = C(t - \text{e}: t-1, t - \text{e}: t-1)$ as the credential zone and the discrimination process array $D_{t,o} = C(t - \text{e}: t-1, t+1: t+o)$ as the probability of a IPS observations, which could lead to a complex event. The score for a time interval (t), with the related parameters, can be calculated as:

$$Score(t,o) = \frac{|\mu(\boldsymbol{D_{t,o}}) - \mu(\boldsymbol{L_t})|}{\sqrt{\text{var}(\boldsymbol{D_{t,o}})/\ \text{a}(\boldsymbol{D_{t,o}}) + \text{var}(\boldsymbol{L_t})/\text{a}(\boldsymbol{L_t})}} \tag{3.5}$$

The μ array is the μ amount for the aggregate vacant entries, and var represents the aggregate vacant entries' variance, and (a) represents the aggregate number of vacant entries. After that, the variation score for the time interval t is:

$$Score(t) = max_{o>o\ min, t+o<k}\, Score(t,o) \tag{3.6}$$

The detection experiments Ire run by utilizing sensed images and data, directed to a classification process through a streaming pattern. The below meta-code script shows phase 1 of the algorithm. The algorithm includes two stages; the first one is termed as the sieving or infiltrate phase; throughout this stage, any questionable event or object occurrence that could produce a complex event goes through the related sequence line awaiting their turn to be processed.

Meta-Code Script 3.1: Complex Event Detection, Phase 1: Sieving Algorithm

```
1 Input: stream of events C = {e1,...en}, max-limit = each
         volume(batch-size)

2 Output: nominated simple event classification (C) after
          feature extraction C = e1, questionable object = q

3 while(q <= n) do
4       for every object vx in C and single occurrence (so)
            in e1 do
5           if vx. labeled = So. labeled afterwards relate vx
                to so as vxos = vx'
6               omit vx from C
7           if the probability of vx' is not than max-limit
                then join vx' to C
8       q = q+1
```

The algorithm separates the dispensable patterns that may not produce a complex event that fulfills the given dictate. The algorithm of CED is stimulated through the observation structures and patterns, which require its stream to be scanned among a specific time interval window. Thus, there is no need to examine the upcoming complex event among the current frame as an alternative to inspecting the whole stream once more. In the second phase, event occurrence refinement, the algorithm searches corresponding to a single occurrence among a particular time window.

Meta-Code Script 3.2: Complex Event Detection, Phase 2: Event Occurrence Refinement Algorithm

```
1   Input: classification and labeling array …
                Lt = C (t - e:t-1, t-e:t-1)
           discrimination process array Dt …
                o = C (t - e:t-1, t+1:t+o)
2   Output: The score of a time interval (t), …
            the variation score of the time interval (t)to
            each complex event

3   for every occurrence of ei   of a questionable event in C
4       do
5       if ei cause to trigger Lj metamorphosis …
           to Lj+1 then include ei in Dt,o
6       if Dt,o <≠ the max limit, then perform algorithm 1
7   for every questionable object = q in series C
8       combine ei to detected complex events group
9       remove from C
10      omit any instance that is not in the …
        specified time interval window
```

The first three lines designate the methodology in which an object gets into the line to be processed, the rest of the line except the last on, depicting the process of detecting complex events via inspection and evaluation process. The detected complex event will be grouped into one set called detected complex events. The below meta-code script shows phase 2 of the algorithm. Just as delineated earlier, event occurrence refinement can identify the presence or existence of complex events that comply with the given principle that must be obeyed. Within this methodology, a series of the nominated simple event are sieved several times with the specified max-limit. Thus, the greater the set limit, the more series are sieved.

3.3. CEP Based Methodology

Since the Cassini–Huygens spacecraft arrived at its destination, it has provided us with images and a huge volume of data that has not been gained at any time before. Almost 13.5 years spent by Cassini's mission in Saturn's orbit Ire the headmost chance to study this anonymous planet charm, which seduces us for a closer look at it, throughout the spacecraft passing near Saturn. (Imaging Science Subsystem) ISS was the RS device that took images of the Saturn system with its moons and rings. 407,302 samples have been included in our analysis, collected from 106 volumes of the ISS data source among 13 subphases of the mission. These phases' duration is very different from just half a dozen samplings to more than one thousand samples. This made us concentrate on just five mission phases, with many samples (see Table 3.6).

Table 3. 6: Analyzed mission phases

Phase Name	Start Sample ID	Start Time	End Sample ID	End Time
APPROACH SCIENCE	1	2004-037T02:07:06.498	10,675	2004-162T14:47:05.854
TOUR PRE-HUYGENS	10,940	2004-164T02:33:51.000	31,640	2004-358T13:47:22.548
TOUR	32,032	2005-015T18:28:29.491	166,187	2008-183T09:17:06.323
EXTENDED MISSION	166,188	2008-183T21:04:09.008	235,887	2010-283T14:14:20.741
EXT-EXT MISSION	235,888	2010-285T05:23:32.745	407,303	2017-257T19:59:04.075

By this stage within the approach gradation, Saturn's planet was huge quiet, so a dual narrow-angle camera was needed to cover the planet's whole size with its rings and some of its icy moons such as Pandora Epimetheus, Mimas, Janus, Prometheus, and Enceladus. A robust approach for recognizing variation has applied to find out if an event has happened in a specific image, based on the difference assessment made with the previous and the following is taken images within three groups of parameters (Group 1: Timing; Group 2: Temperature; Group 3: communication) and its related 15 variables of metadata. The analyzed variables sets are given in Table 3.7.

A commonly unanimous convention specifies the categories that the event is recognized based on the number of significant attributes, e.g., a change in size or the color and even the previous known shape. The connection between events within the conditional probability scope commonly holds a conditional likelihood provided that an event conditional distribution continues to be fixed with the given measures.

Table 3. 7: Groups of analyzed variables

Variable Group	Variable Name	Description
A. Timing	IMAGE_NUMBER	µ time of image
	START_TIME	Capture start time of the sample
	END_TIME	Capture end time of the sample
	EARTH_RECEIVED_START_TIME	Start time of the receiving msg.
	EARTH_RECEIVED_END_TIME	End time of the receiving msg.
B. Temperature	FILTER_TEMPERATURE	Temp. of the optics filter [°C]
	OPTICS_TEMPERATURE_FRONT	Temp. of the front optics [°C]
	OPTICS_TEMPERATURE_REAR	Temp. of the rear optics [°C]
	DETECTOR_TEMPERATURE	Temp. of the detector [°C]
	SENSOR_HEAD_ELEC_TEMPERAT	Temp. of the head electronics [°C]
C. Communication and scale	EXPECTED_PACKETS	No. of expected radio packets
	INSTRUMENT_DATA_RATE	Data rate of the transmitter [kb/s]
	INST_CMPRS_RATIO	Compression ratio of the msg.
	RECEIVED_PACKETS	No. of received radio packets
	PIXEL_SCALE	Pixel scale [km/pixel]

The nominated approach acclimates supervised learning. The method must impart visual significances pertinent to a particular event class by extracting the whole related visual motif and patterns for the approach, including constructing a IPS array for the related target metadata time series. A set of the weighted score for each submission and a sensitivity threshold value is detected. Simultaneously, the consecutive window size specifies the method's correctness via the difference of the time moments and intervals. After that, an alteration score for each timestamp is computed based on the IPS score array. A time series can be defined as a data concatenation of marks gathered over a period of time.

3.3.1. Special Event Detection Algorithm

The concept of processing a complex event is concerned with the issue of processing several events with the attention of pointing out the significant events among a timely stream of events sequence. Introducing the label of weight with the event provides a numeric value that quantifies the degree of compactness of an event. This weight spans with a range of 0 till 1. The weight is like a temporal dialectic with a sensible way concerning events and their impacts. Aiming to promote the detection process's competence with a scale modality, I have introduced the concept of weighted Complex Event Level (wCEL), which is an extension of a weighted complex event. Script of algorithm meta-code is illustrated in Meta-Code Script 3.3:

where parameter ρ is the sensitivity, and d is the memory of the Special Event Detection (SED) mechanism. The service specialist gives both parameters. It can be observed that for $\rho = 0$ each sample $Y(t)$ is an outlier and for $\rho \geq \rho^*$ no outlier will exist. I name ρ^* cut the value of the SED sensitivity.

Meta-Code Script 3.3: Special Event Detection Algorithm

```
1 Input:  Y(t) with t ∈ (1, N)
2 Output: Special events of variable Y(t) are considered
          outliers of Y(t) and are stored in the corresponding
          variable, V(t)

3 while t = 0, V(1:N) = 0
4     for d of consecutive samples generating vector Y(t:t + d)
          and average value mY(t, d) = μ(Y(t:t + d)) and …
          σ(t, d) = SD(Y(t:t + d))

5         Set element V(t + d) corresp. to element Y(t + d) of

          the time series to be outlier (i.e. V(t + d) = 1):

          if following relation hold: …
              |Y(t + d) − mY(t, d)| ≥ ρ · σ(t, d)
6             for (t = t + 1) (Go through line 5) Until t > N.
7 print(output)
```

Special events of variable $Y(t)$ are considered outliers of $Y(t)$ and are stored in the corresponding variable, $V(t)$. Conform to relation (3.7) $V(t)$ has the following property for each $t = 1, \dots, N$:

$$V(t) = \begin{cases} 0 & if\ Y(t) \text{ is } ordinary\ event \\ 1 & if\ Y(t) \text{ is } special\ event \end{cases} \tag{3.7}$$

First, d elements of the variable are ordinary events.

3.3.2. Calculation of Weighted Complex Event Level Metric

For a group of values $G_k(t{:}t + d) = \{Y_1(t{:}t + d), Y_2(t{:}t + d), \dots, \{Y_k(t{:}t + d)\}$ can be determined the Weighted Complex Event Level conform to the following meta-code algorithm in script 3.4:

Based on line number 4 of the meta-code I have:

$$\sum_{i=1}^{k} \frac{w_i(t+d)}{w(t+d)} = 1 \tag{3.8}$$

Meta-Code Script 3.4: Weighted Complex Event Level Metric Calculation

1 **Input:** $G_k(t{:}\,t+d) = \{Y_1(t{:}\,t+d), Y_2(t{:}\,t+d), \dots, \{Y_k(t{:}\,t+d)\}$
2 **Output:** Weighted Complex Event Level

3 **while** $t = 0,\ i = 1$
4 $\quad w_i(t+d) = \sum_{j=t}^{t+d} V_i(j)$ and $w(t+d) = \sum_{j=1}^{k} w_i(t+d)$
5 $\quad$ **for** $(i = i+1)$ (step 4) Until $i > k$
$\qquad wCEL(G_k, t+d) = \sum_{i=1}^{k} \frac{w_i(t+d)}{w(t+d)} V(i)$
6 $\quad$ **for** $(t = t+1)$ and (Goto step ii) Until $(t > N)$
$\qquad wCEL(G_k, t+d)$ is a metric of event complexity and has Limited values: $wCEL(G_k, t+d) \in [0,1]$
7 **print**(output)

And it conforms to formula (3.7) values of $V(t)$ are special: $V(t) \in [0,1]$. This feature together with relation (3.9) implies the relation in line 10 of the meta-code. The higher is the number of special events in the group $G_k(t{:}\,t+d)$, the greater is the $wCEL(G_k, t+d)$. The higher is the special events in the group G_k in sampling moment $(t+d)$, the greater is the metric $wCEL(G_k, t+d)$. It is intended to characterize a given group G_k of variables globally, independently of the time. For this, I determines the µ of weighted Complex Event Level by the following formula:

$$mwCEL(G_k) = \frac{\sum_{t=d}^{N} wCEL(G_k, t)}{N-d+1} \tag{3.9}$$

This metric depends on the sensitivity, ρ and memory, d of the SED mechanism and globally characterize the variable group G_k.

3.4. Constructive Knowledge Based Event Methodology

Objects detection has always procured a significant volume of attention from analysts and researchers since Deep Neural Network Systems (DNNs) have been competent for accomplishing in the vicinity of human-level rendering [109]. Exploiting (DNNs) inside a constructive scheme contains a centrality that permits clamor reluctance and present error recovery. Moreover, these networks are qualified to memorize the input modality or structure that does not require earlier information. CKE distinguishing proof demonstrates slants for both consolidation and constancy for the classification process. Developed three decades ago, multilayer RNNs have the lion's share of frequently utilized DL methods [110]. These kinds of neural networks possess a memory that registers the data that they have dealt with before. Furthermore, RNN is a robust method for handling sequential data [111], and they utilize the former output to predict the following output. In such circumstances, the RNNs have recurrent loops. Those loops are among the hidden neurons, which permits keeping the former input data for a period. As a result, the model gains the ability to predict the forthcoming output. The output generated by the hidden layer is resent (τ) times toward the hidden layer. The neuron's recursive outcome is forwarded to the subsequent layer whenever the cycle of iterations is accomplished. With the current status, the output is more inclusive, and the former information is preserved for a prolonged period. Eventually, the errors will be sent inversely to bring up to date weights. To treat the prominent temporal overreliance, the RNN is a logical option concerning the net-work recurrent connections, which let the network recall memories of former inputs [112]. Figure 3.4 represents a notational LSTM layout.

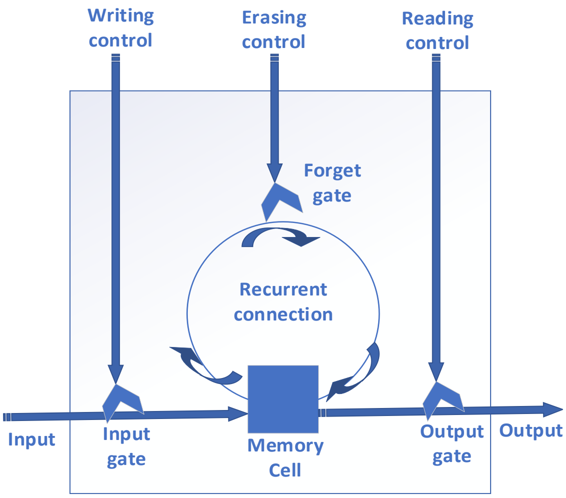


Figure 3. 4: LSTM layout (notional)

Nevertheless, typical RNN does not tend to impart on-term time overreliance due to the gradient vanishing dilemma. LSTM can overcome this issue by put to use the featured memory cells structure. Via stacking memory cells, previous data inputs could be stored in the output to a certain extent, conveyed by cell state. It should be mentioned that this research is a resumption of past investigation exertion associated with the C-H project dataset [100, 111].

CEP and discovery are an extravagant ponder space escorted with numerous limits to be hypothesized, the profiteering of learning approaches to arrange and uncover uncommon events proffer a gigantic tolerable to be utilized on another external space voyages. The colossal mileage space between the Earth terminal and the shuttle requires vital time, which suggests that the reaction to any occasion might not be carried out amid the requisite period of time [100]. One of the significant ponders discourse around Constructive modeling concerning if the computer can perform insights modeling as the human does. Intellectuals customarily show to the limitations on what may be considered computable indeed come to proposing that human insights might not be computational. Be that as it may, a few parties get these contentions as captivating, and they consider that they do not indeed hold an eminent impact on the conducted endeavors of modeling. Whereas, in other regards, there are hypothetical results from information preparation and computational concepts that have had a colossal impact on the development of constructive modeling. Figure 3.5 shows the pattern classification procedure.

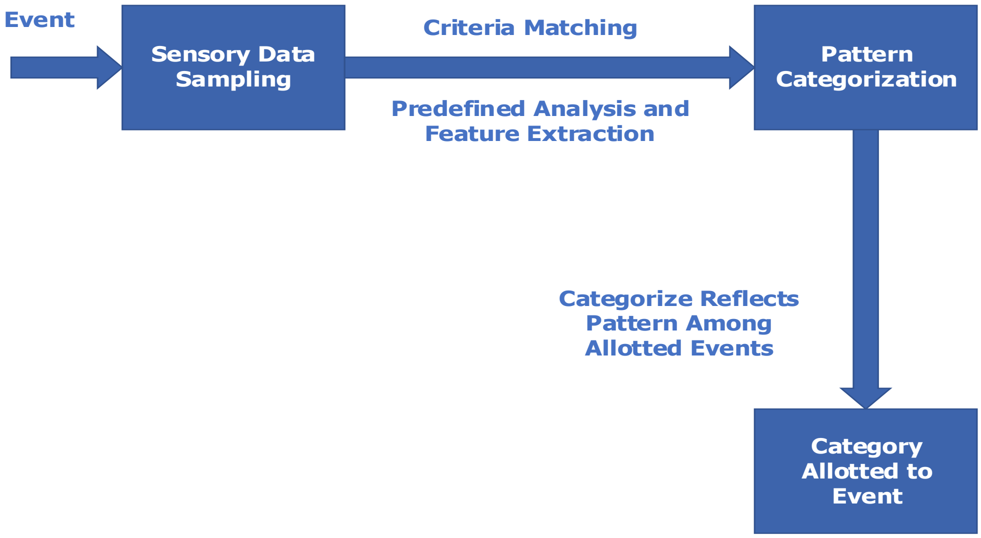


Figure 3. 5: Classification of sampled patterns

The broadscale point in pattern classification is to postulate the denomination of a method and to construe the detected information to the demonstrated design for the suggested model of CKE appears in Figure 3.6. The framework secures the information and stats with the method of analyzing this information and recognizes the event within the data at that point, an additional assessment, and preparing to distinguish the uncommon (special) events among these occasions. The model presents the concept of splitting the available dataset into two primary (representative, large enough) subsets: a training set, a subset used for training. While the test set— is a subset that is utilized for model testing. Within ML, the significance of model validation can be indicated as an approach at which the trained model will be evaluated through the dataset of testing. The data set of testing is an autonomous part of the original dataset that includes the training portion. The principal aim of carrying out the testing process is to examine the trained model generalization competence [100]. The approach function starts to undertake the mode of perception reasoning afterward, the framework keeps the outcome in its learning repository for the following reasoning phases, the subsequent phase of the model includes heading to the constructive categorization stage, and its task is to appoint the complex events depending on this reasoning process of categorization. A detailed illustration of the proposed approach is given below:

1. Sensory inputs: sensors for planetary data that contain measurement and readings making up huge sensory data, including delineating from an autonomous modality depiction that will go through the event detection process among the observed data, overlook clamor in arrange to attain the specified match of demonstrating complexity. These sensory data are required to fulfill and maximize the utilization of the valuable gathered data. I'm providing a model of AI using this sensed data to allocate events and detecting special events, and then this data enters a process of cognition and classification to detect complex events.

2. Event Detection Module: the provided event detection module extraordinarily complies with the pipeline processing in steps. To determine the complex event for many-scale categorization, I make practical and effective use of stacked bidirectional

LSTM [113]. The method assumes that autonomous input is not only a one-dimensional vector. Also, it could be multidimensional tensors likewise. To integrate such objects, I'm utilizing tensor normalization.

3. Special Event Detection Module: such detection in a vast data set is often possible advance for information examination, and elucidation than just an explicitly stated modality, particularly within the technique of multivariate investigation time arrangement, within the situation of a deviation among the conventional disposal is recognized. A special event could be characterized depending on the limit (max-limit), followed by many labels that identify particular modalities such as receiving start and stop time, temperature, and packet receiving rate.

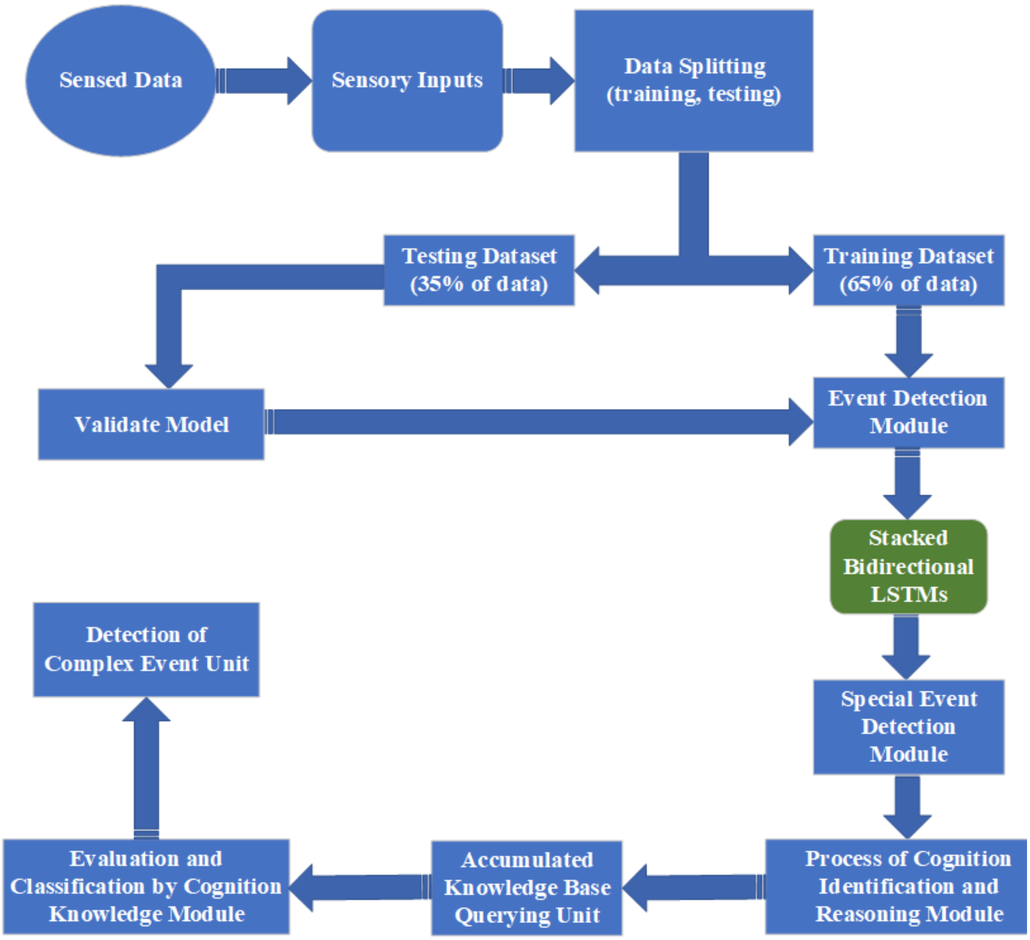


Figure 3. 6: The architecture modeling process of CKE

4. Process of Cognition Identification and Reasoning Module: cognition is an

intellectual handle of doing something regularly to attain a point of getting information through thought, observation or experience (an occurrence or event), and detecting. It joins various particular properties of mental occupation, thinking, reasoning, and assessment. Constructive reasoning and recognizable proof include modality distinguishing event components, incorporating its qualities and information sorts such as perceptions and modality observations. This module utilizes existing facts, information, and recognition to produce not existing before(unprecedented) knowledge.

5. Accumulated Knowledge Base Querying unit: the previous knowledge-based approach of constructive dialectics usually pays attention to the classification viewpoint because of the tremendous extent of the dataset. This unit creates a preparing series from the former generated information. The querying unit process incorporates the method of query and reminiscence, which is assigned to the stacked bidirectional LSTM [114]. In arrange to obtain improved execution by settling the associated matters to the inquiry by collecting various outcomes-sets created from past inquiries.

6. Evaluation and Classification by Cognition Knowledge Module: The classification module needs a precise merits extraction to extricate intricate merits. The classification process is predominant within the space of data frameworks. Classification reduces the complexity of executing among individual module parts as a replacement of being have to recall each merit of every component. Classification reduces the complexity of executing among individual module parts as a replacement of being have to recall each merit of every component.

7. Detection of Complex Event Unit: a complex event is made by analyzing extraordinary (special events) by utilizing many parameters. Like the level of the identified changes within the modality, as each extraordinary event is associated with all intervals of times that mention its occurrence span term. Concerning special events, the related time interval is considered a measure that gives the starting and wrapping up the point of the uncommon event. Whereas with complex events, the apportioned time intervals contain the duration or the parcels of time of the full sub-events. These cognitive intervals are ideal for gathering the fundamental extraordinary (special events).

3.5. Meta-Learner Long-Short Term Memory Network Methodology

The meta-learning approach proposed in [115] and [116] works via executing a few-shot dataset sampling from an intended task and acclimating the approach inner portrayals among gradient descent specific steps. It must be stated that this research is a supplement of past investigation exertion associated with the C-H project dataset [95, 100, 109]. Recurrent Model Meta-Learning is a part of the adopted model tailored to LSTM. With this sub-framework, the algorithm of meta-learning shall train the LSTM model, which in its part must perform the needed dataset processing consecutively, and subsequently process the incoming data as new inputs to the softmax classifier, which requires passing the extracted features with the (image, label) pairs set for each batch of the dataset.

The adopted framework, as shown in Figure (2), includes three modules, a features extractor (G), a meta-learner LSTM (M), and map-reducer discriminator (D), all of them are acquiring the knowledge altogether. From one side, I anticipate the features extractor (G) to extract all the related data during its task by capturing high valued features, which will clue the meta-learner LSTM (M) to carry out. On the other side, it is logical that the features extractor (G) will be reinforced via the map-reducer discriminator (D) over consequent tasks on a Big data Bd. After dealing with a massive number of data and its features, the features extractor (G) progressively learns and acquires the knowledge to extract features from raw image data; this mapping process will considerably facilitate the meta-learning implementation. By considering the domain Bd of possible experiences ET by arithmetic approach, I devise the subsequent optimization issue in (3.10) methodically:

$$min_{\theta G,\theta M,\theta D}\ E_{T\sim p(T),(X,Y)\sim Bd}[J(LT(\theta_{M,}\ \theta_G), L_{(X,Y)}\ (\theta_{D,}\ \theta_G))] \qquad (3.10)$$

where $\theta G, \theta M, and\ \theta D$ represent the congruent modules parameters. The task of meta-learning (T) has a distribution $p(T)$, while (X, Y) symbolizes a sampled labeled instance from the Bd. The purpose is to decrease the joint expectation indicated by J. This joint will be applied on both losses: the loss $LT(\theta_{M,}\ \theta_G)$, which is related to the task of meta-learning, and on the loss $L_{(X,Y)}\ (\theta_{D,}\ \theta_G)$ which is related to map-reducer discriminator (D). A meta-learner can also commence a learner to bring up to date learner via gradient descent, which has a steady learning rate (R) over every task, gradient descent begins from incipient parameters θ_0 and afterward, it carries out the subsequent update in equation (3.11):

$$\theta_t = \theta_{t-1} - R\nabla_{\theta t-1}\ L_t \qquad (3.11)$$

The previous equation is utterly analogical to the cell state update of the LSTM. With each meta-learning process epochs, the associated task includes a training set [train (T)] and another one for testing [test (T)]. For the map-reducer discriminator (D), it should eliminate identical images or batches among the Bd and provide labeled batches and images. The map-reducer discriminator (D) and the meta-learner LSTM (M) have a joint loss with the purpose of reducing the expected loss with the task of map-reducer discrimination:

$$L_{(X,Y)}(\theta_{D,}\ \theta_G) = Ls(D\ \circ\ G(X), Y) \qquad (3.12)$$

where Ls can be any appropriate loss function for map-reducer discrimination, the features extractor (G) is supplied with the required training to extract the needed data from the image batches, while meta-learner obtained experience and learned to carry out the image and batch labeling. The map-reducer discriminator (D), which has given the parameter θD, is intended to foretell image labels created by G, and it is performed via gated neural networks. The features extractor (G) has given the parameter θG and is carried out via gated neural networks. The meta-learner LSTM (M) has given the parameter θM, and its mission is to gain the knowledge and pass from a task(T) to another among the training process. Over any provided task (T), the related concepts include meta-learner (M) that adjusts a learner AT for a given task with a specific aim, which is to reduce the anticipated loss with the task of meta-learning, and provided by equation (3.13):

$$LT(\theta_{M,}\ \theta_G) = \frac{1}{|test(T)|} \sum_{(x,y)\in test(T)} Ls(AT\ \circ\ G(x), y) \qquad (3.13)$$

Implementing softmax on a huge dataset produces a more reliable LSTM for classification. Ordinarily, softmax function formula (3.14) is utilized by:

$$P_k = \frac{\exp(\mathrm{Vk})}{\sum_{\mathbf{n=1}}^{\mathbf{k}} \exp(\mathrm{Vn})} \tag{3.14}$$

where Pk indicates the chance or the probability that the vector k is a part of a group termed as class v. In multiclass classification, there is a need to compute the loss related to every class label for each process observation, and the outcome can be aggregated as a sum by cross-entropy, which is expressed by equation (3.15).

$$CE = -\sum_{k=1}^{Z} Bc \; log \;\; P_k \tag{3.15}$$

where Z- represents the number of classes that may include (Saturn, Rings, Titan, Icy Satellites, Small Satellites (rocks), Sky), the log indicates the traditional log. At the same time, B is a binary reference (1 or 0) that shows whether a class label k is the proper classification for a given observation.

The indicator P represents the predicted probability of a given observation that belongs to a class k. The proposed network is indoctrinated to present the result vector k near its related one-hot vector to reduce cross-entropy loss. The stochastic gradient descent algorithm could be utilized to optimize the previous aims, but with our thematic model, I generated a modified version of the stochastic gradient descent method. The elaborated approach is summarized below in Figure 3.7.

It is crucial to pay attention that the right results of the target vectors within the network are steady throughout the training process. After representing the framework, among deep meta-learning LSTM, the phase of illustrating our harmonized algorithm is necessary. The upper section indicates the set of meta training D(meta-train), where each numbered box represents a different batch of the Bd that is composed of the training set denoted as Dtrain and Dtest. The meta-test set which is indicated in the illustration with D(meta-test) is also demonstrated in the same method, but via a various dataset that includes batches that are not available in any of the other batches in D(meta-train). Furthermore, there is a set of meta-validation which is exploited to specify additional labels and features.

The adopted framework is presented in Figure 3.8. I acquired the revelation algorithm by gradient descent represented in equation (3.10), if I assumed that there is a learner classification process with parameters θ which it needs to be trained on the set Dtrain.

The decisive algorithm which makes the best or most effective use of (a situation, opportunity, or resource) and also exploited to train the neural classifier is approximately divergent of gradient descent, that utilizes updates, where the expression of the (θt−1) represents learner parameters in accordance with (t-1) updates, and (R) which is obtained during the time period t, Lt denotes the loss, which is brought to optimization via the learner through nth number of update, ∇θt−1 Lt specifies loss gradient corresponding to the associated parameters θt−1, and θt demonstrates the learner updated parameters, the pivotal rumination that I parameterized at this spot this update which has common features that look or seem like LSTM cell state.

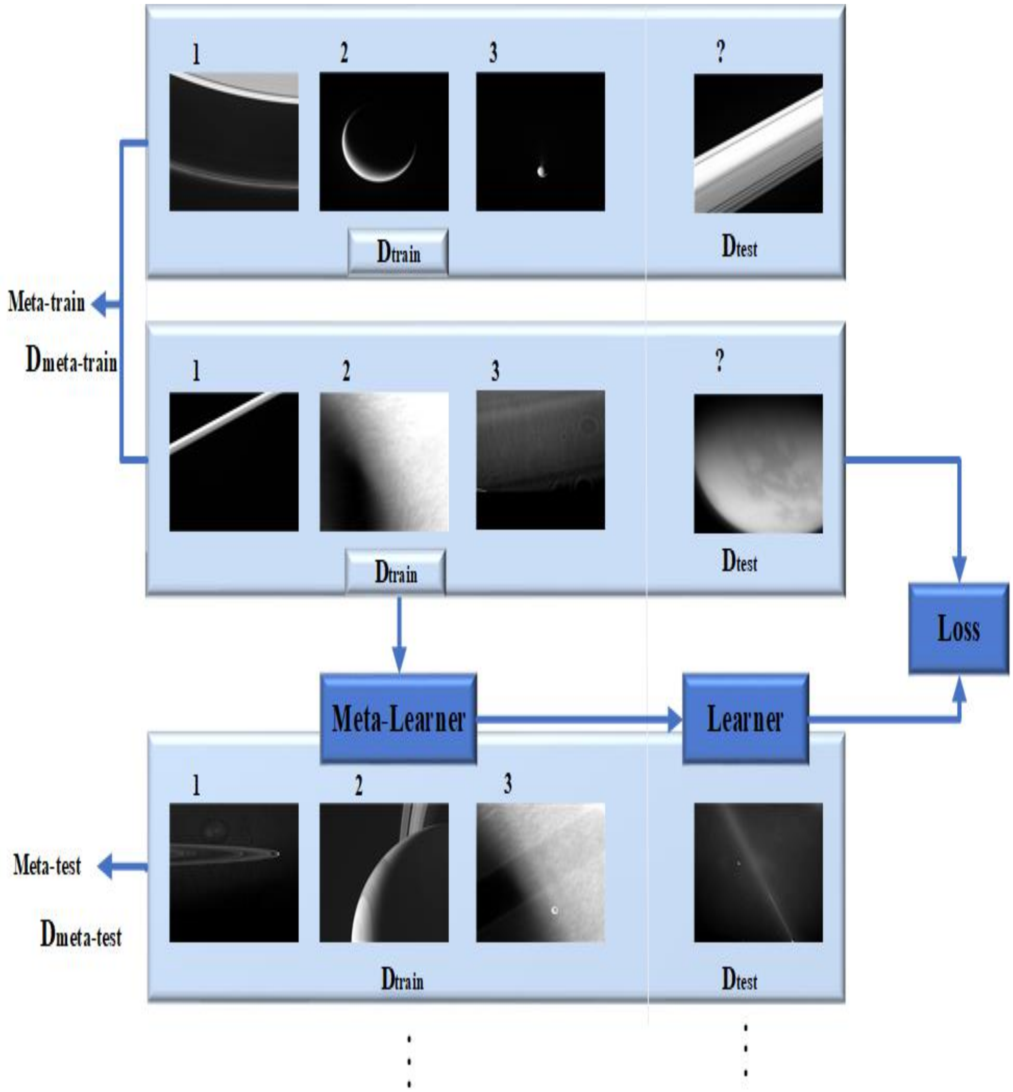


Figure 3. 7: Illustration of Meta-learning layout

There are several parameters of similarity which could be exploited within our approach. I consider the process of image classification by analyzing several parameters as a preprocessing phase for image classification and analyses of a block of tensors via layered Map-Reduce (LMR) for image patches classification where these investigation processes passed into (LSTM) blocks. I'm using the LSTMs block unit to exploit the memory dependencies component to regulate the information flow; as I deal with a Bd meta-learning, LSTM is a perfect choice.

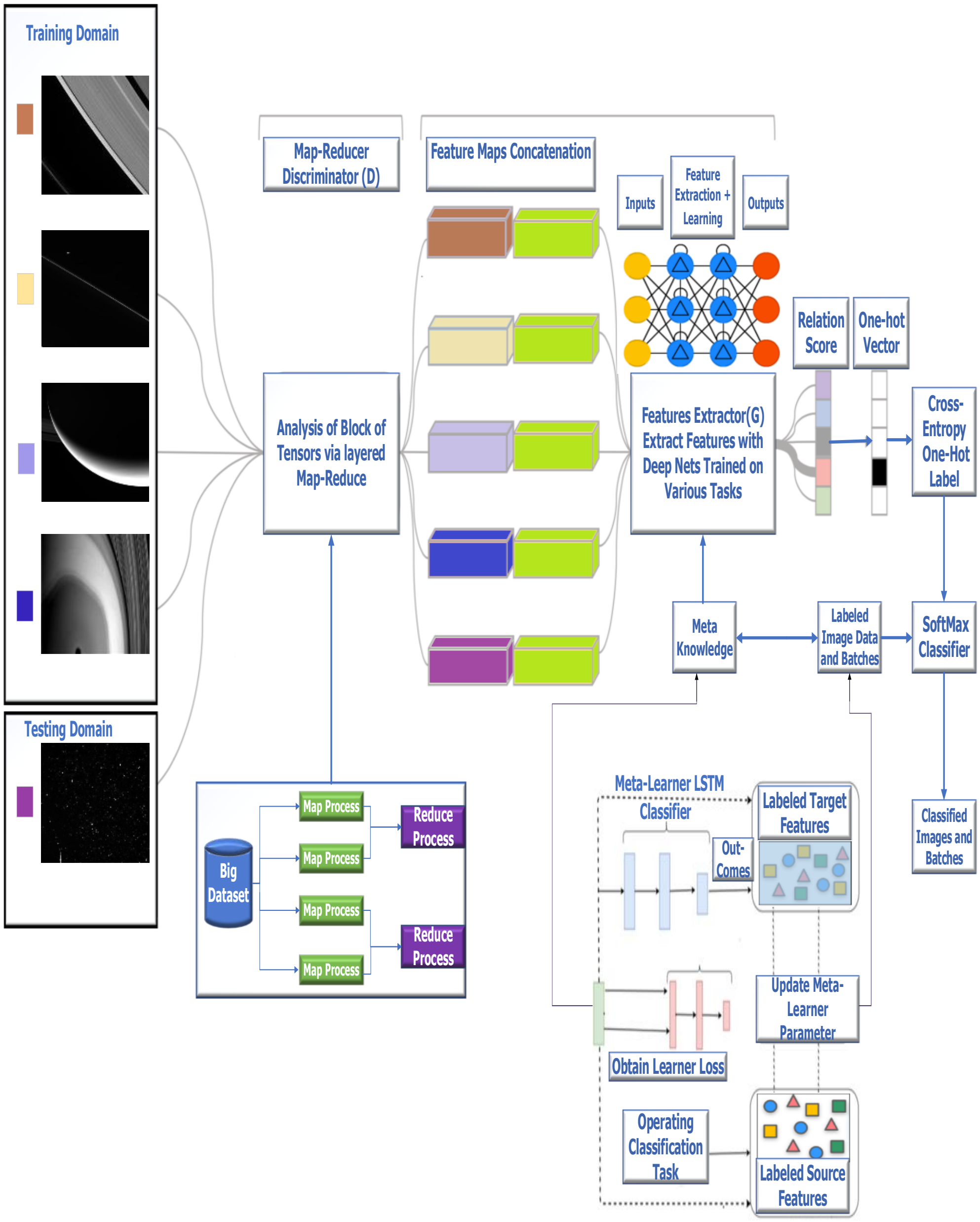


Figure 3. 8: Overview of the adopted framework

The prime factor to DL's prosperity is its potentiality towards acquiring knowledge from hierarchical features via enormous amounts of raw data such as text or images. Extracted features through DL methods have been confirmed to be outstanding and better than traditional approaches in many different aspects, such as preciseness and reduced resource challenging [117].

3.6. Development of Learning-Based Approach for Detecting Trajectory Modifications

The connotation of a complex event is tied up with the matters of processing multiple events accompanied by paying attention to mark out distinct events within a timely tributary of events [100]. There are cases where the available information to depict any process or system is just an inspection of the observations. For the scope of big data, there is a remarkable denomination of the issue, which is to recognize an extreme event [118]. The spacecraft launched in October 1997 from the Earth arrived at Saturn on 1 July 2004 [119]. This event is named SOI of the spacecraft C-H. It required the spacecraft 6.7 years from the Earth's launch to reach its destination SOI at Saturn. The flybys generated by the gravity-assistance of the various planets are intended to boost the spacecraft's velocity proportionally to the Sun. Cassini also derives benefit from Saturn's most giant moon's gravity, Titan, to be as a pivot point in favor of its major trajectory modifications [3]. Cassini's prime engine was required to slow down or stop the spacecraft using a brake and allow Cassini to be situated into Saturn orbit upon the approaching in 2004. The flight path of the orbiter was disposed to move away from the Saturn rings plane. This variation concerning the viewing geometry drove many unprecedented findings of formerly invisible ring kinetics and their atmospheric events, especially that take place at poles of Saturn.

The below visualization Figure 3.9 represents the last 393,977 trajectory samples of the Cassini's flight path situated between planets. This last 13.5 years of the trajectory, represented by approximately semi-ellipse in the large scale and analyzed by us, start with a circle shape in the bottom, while the square on the top symbolizes the end of the trajectory on 14 September 2017. The Sun, the first sample, and the last sample are marked with a star, circle, and square characters, respectively.

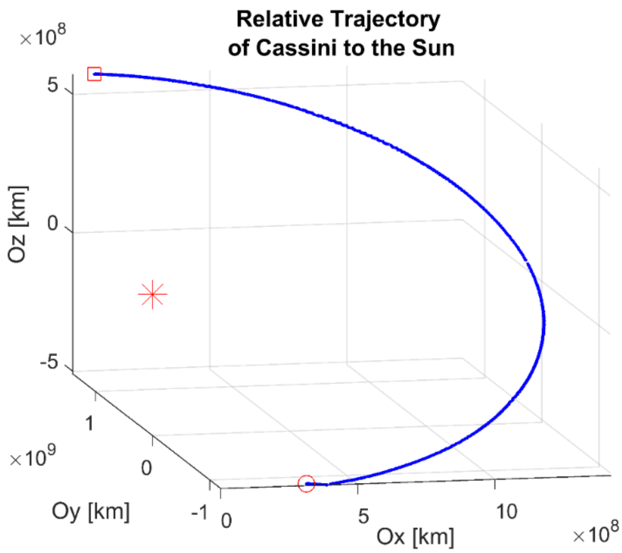


Figure 3. 9: Cassini large scale trajectory around the Sun

The trajectory represented contains just the last 13.5 years, including the approaching phase, SOI event, and rotating around the Saturn of Cassini spacecraft. This period is approximately half the period time of the Saturn trajectory around the Sun.

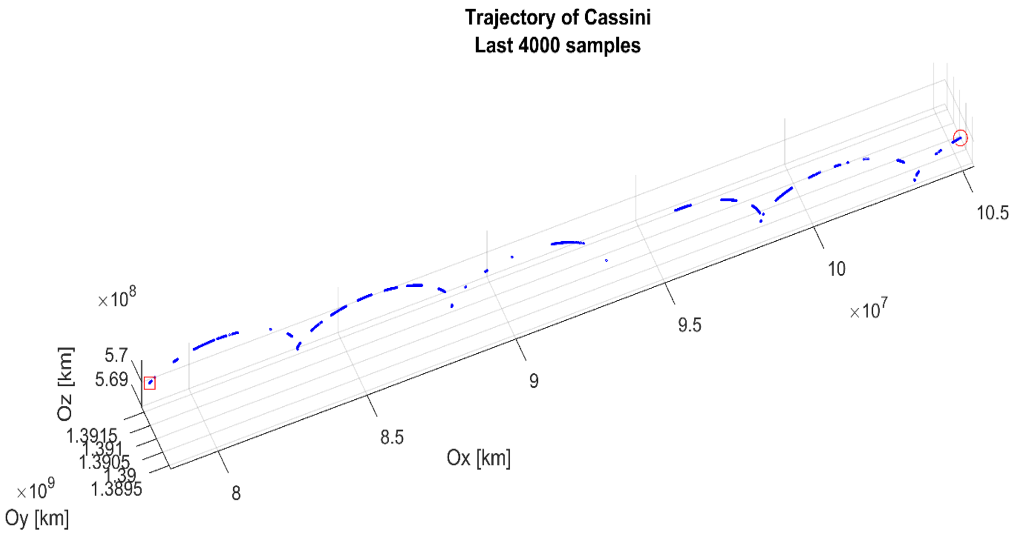


Figure 3. 10: The last 4000 samples of Cassini's small-scale trajectory

The Cassini trajectory after the SOI is a complex curve compound by an ellipse- based helicoid around the Saturn, which moves on the own ellipse curve around the Sun. Figure 3.10 Shows Cassini trajectory for the last 4k samples; the starting and the endpoint are represented with the red circle and square, respectively. The last sample is represented on the left-hand side by the red square. Gaps of the plotted helicoid trajectory should be observed because of the non-periodic sampling process controlled by the Earth's project team. Because of the non-periodic communication between the Earth and Cassini, the spacecraft's trajectory coordinates contain smaller or higher gaps. This makes it non-trivial to detect modifications of the trajectory. I seek to detect offline events related to Cassini spacecraft trajectory modifications with the developed approach. For this aim, I put forward our model that utilizes Long-Short Term Memory neural networks to elicit valuable data and learn the time series inner data pattern and exploit the LSTM potential regarding memory dependencies.

3.6.1. Extracting Sampling and Trajectory Characteristics of the C-H Database

The spacecraft had two parts: HP and CO. C-H arrived at orbit around Saturn in 2004, transmitting precious data back to the Earth. Huygens step inside Titan's atmosphere, the massive moon of Saturn, fall downward through a parachute to the furthest point so far, land on its surface, take samples, analyze them, and send the results to Cassini, forwarded them later to the Earth. Cassini instruments of RS collected data remotely from enormous distances. The propagation time of the electric signal between the Earth and Cassini took around 80 minutes. After twenty years spent in outer space, the orbiter "Cassini" drained out of energy. Cassini was immersed into Saturn's atmosphere on 15 of September 2017, and this is how the mission ended. The ISS of NASA generated the acquired image data. The ISS is composed of 2 detached cameras wide-angle camera and a narrow-angle camera. ISS image volumes dataset is composed of a huge number of images and their related labels that hold the images' metadata. The data set is publicly available at the reference [120]. The 116 volumes of the data set analyzed by us Ire downloaded from the NASA source mentioned above. The staring sample has time stamp 02:07:06 on 6 February 2004, and the end stamps 19:59:03 on 14 September 2017, both explained in UTC (Coordinated Universal Time). The most important events of the project are given in Table 3.8. During the C-H project's five main objectives (i.e., research of Saturn, moon Titan, rings of Saturn, icy satellites, and magnetosphere), there was necessary execution of trajectory maneuvers. The number of planned and executed modifications of the trajectory for each mission is given in reference [121]. The ratio of the number of executed and planned trajectory maneuvers is 69.5% and 67.3% for the Prime and Equinox mission, respectively. Having no official information about the executed trajectory modifications in the Solstice mission, our prognosis is 68.4% (average of the previous two) of the planned maneuvers, giving

Table 3. 8: Tasks time stamps of main phases (UTC)

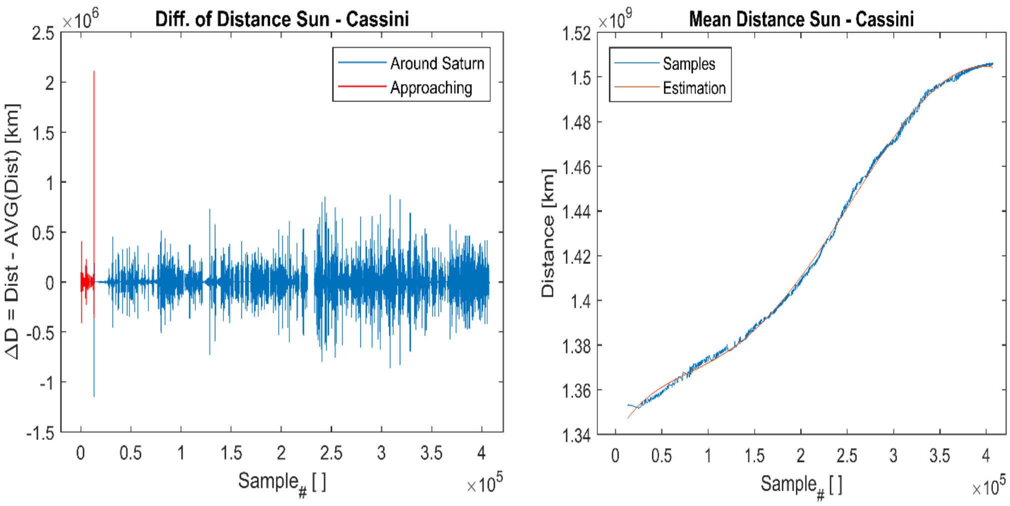
Task	Starting Date	Ending Date
C_H Project	15 October 1997	15 September 2017
Analyzed DB	6 February 2004	15 September 2017
Prime Mission	1 July 2004	1 July 2008
Equinox Mission	1 July 2008	11 October 2010
Solstice Mission	11 October 2010	15 September 2017

a number of 141 trajectory modifications. Table 3.9 provides the number of Saturn orbits along with the planned and executed maneuvers. The invariable plane concerning the planetary framework is the plane crossing over its barycentre, known as the center of the mass.

Table 3.9: Number of Saturn orbits and maneuvers

Mission	No. of Orbits	Trajectory Maneuvers Planned	Trajectory Maneuvers Executed
Prime	75	161	112
Equinox	64	104	70
Solstice	155	206	141

Accordingly, the invariable plane [122] is described as the vertical to the overall angular vector of the quantity of motion of a moving body in the solar system, which moves over its barycentre. So, based on that being steady, it offers a perpetual instinctive reference plane, with the fact that the ecliptic partially shifts with time. C-H data set downloaded from the NASA web site contains N = 407,303 samples. These data refer to the last 13.5 years of the interplanetary mission in the time interval [16-Feb-2004, 15-Sep-2017]. Data capturing Ire executed in different phases and sub-phases of the project. Each sub-phase has several sequences where each sequence has a number of observations depending on the decision of project leaders. An observation contains a set of samplings where the set size depends on the technological events of the spacecraft or astronomical events around Saturn. The number of sequences and number of observations in the analyzed time period by us was 2,355 and 10,851, respectively. The propulsion system is used to change the spacecraft's course to meet science nearing the expected goals. The gap in distance values between samples 225,900 (24-Jun-2010) and 232,800 (30-Aug-2010) is caused by the long duration of the data reception missing. The modification of the Sun-Cassini distance can be observer by the small spikes in Figure 3.11a, too.



(a) *(b)*

Figure 3. 11: High scale Cassini-Sun distance during the DB samples

The sampling moments of the sensor values by Cassini was not periodic during the project duration. The heat produced from the natural decay is transformed into electricity by solid-state thermal adapters, allowing spacecraft to work at large distances from the sun. While the µ distance between the Sun and Cassini over samples is given in Figure 3.11b. To illustrate the change that is happening within Cassini velocity, I represent Figure 3.12, which details the SOI process.

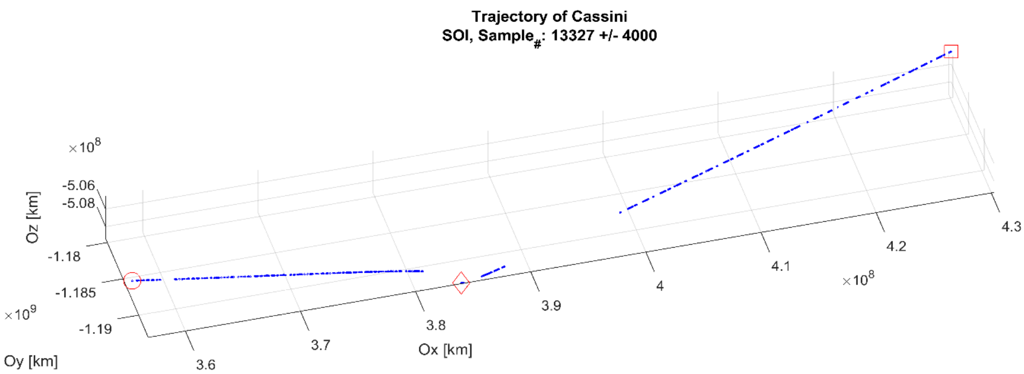


Figure 3. 12: The large-scale trajectory of Cassini around the SOI process

The trajectory in a smaller distance scale is a helicoid with an ellipse in cross-section view to the Saturn orbit. At the same time, an engine firing was initiated to decrease Cassini velocity. The maneuver of SOI took roughly ninety minutes, let the spacecraft be caught via Saturn's gravity and enter an orbit with five months period long. The red circle is the starting moment of the interval. The diamond mark represents the insertion point SOI of the Cassini around Saturn orbit. The red circle is the starting moment of the interval. The diamond mark represents the insertion point (SOI) of the Cassini around Saturn. The time interval between spikes of the curves represents the variable period of the helicoid orbiter around Saturn. Velocity magnitude at the beginning and the end of each mission is represented with a black filled dot and square objects, respectively. Cassini's magnitude of the instantaneous velocity is provided in Figures 3.13.

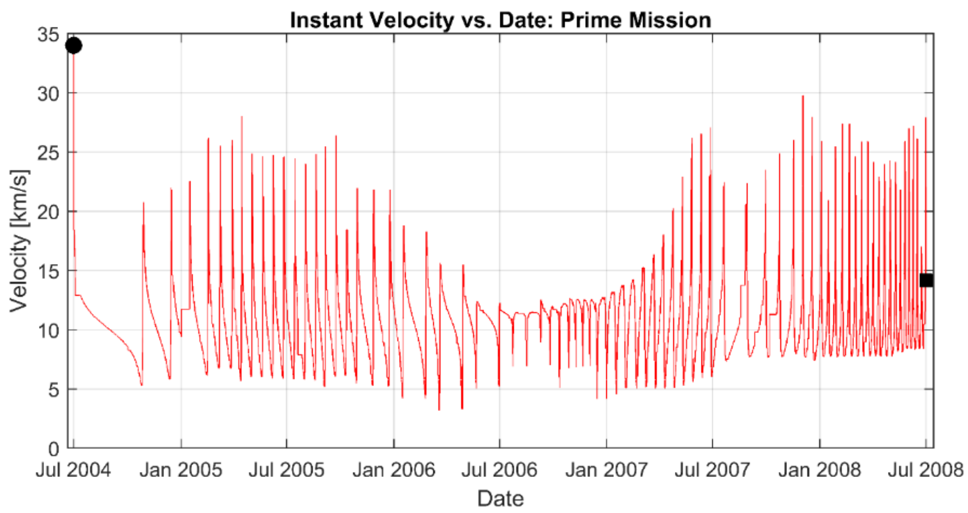


Figure 3. 13: Cassini instant velocity magnitude to the solar system during the Prime mission

Velocity magnitude at the beginning and the end of each mission is represented with a black filled dot and square objects, severally. The velocity of Cassini concerning Saturn fluctuated from 12.5 km/s to 18.5 km/s conform to [123]. Our analysis based on the NASA database resulted in velocity values to the solar system 3.18… 29.75 km/s.

3.6.2. Conditions of the Complex Event Detection of the Cassini Trajectory

The main aim behind applying our classifier is to specify complex events from sensory generated data. To detect temporal semantics for complex event recognition, I prolonged the time index of the sensory data. Potential complex events of the data set are in the moment of change of observation sequences. I consider extreme modification of the trajectory when the CO velocity vector changes more than a threshold metric. Because the velocity is a measure vector, extreme events in the trajectory imply fulfilling any of the following two conditions: extreme modification of the velocity direction or the acceleration vector's magnitude.

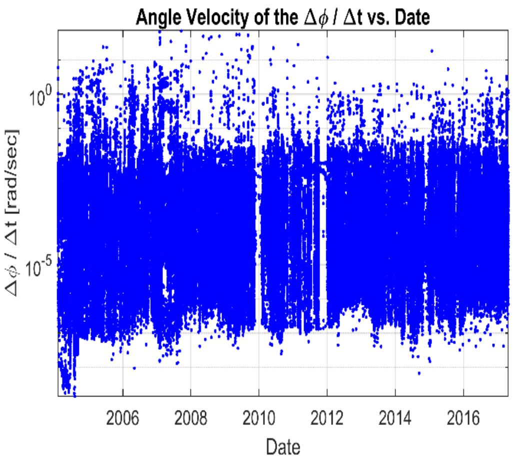
Modification of the Velocity Vector Direction

The expense of spacecraft launch is usually determined by the change in the velocity vector necessary to reach the target orbit. The velocity of the angle modification $\Delta\phi_i$ between consecutive velocity vectors v_i and v_{i+1} is given by the following formula:

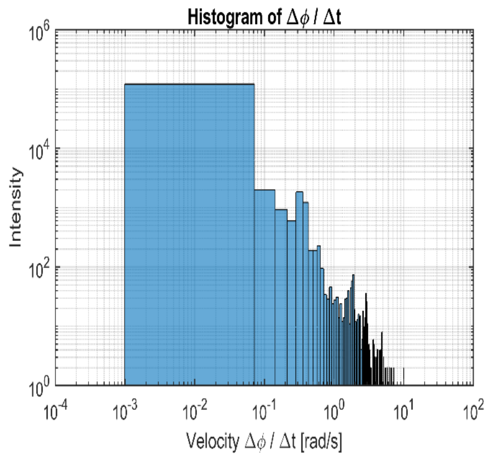
$$\frac{\Delta\phi_i}{\Delta t_i} = \frac{\operatorname{acos}\left(\frac{\overline{v_{i+1}} \cdot \overline{v_i}}{\|\overline{v_i}\| \cdot \|\overline{v_{i+1}}\|}\right)}{t_{i+1} - t_i}, \quad i = 1,2,\dots,N-1 \tag{3.16}$$

where $\overline{v_i}$ and $\overline{v_{i+1}}$ are two consecutive velocity vectors of the orbiter, $\|\overline{v_i}\|$ is the magnitude of the vector, Δt_i is the time interval between two consecutive samplings, and $i = 1, 2, \dots, N-1$. The number of vectors is the total number of samples in the Prime, Equinox, and Solstice missions: $N = 407{,}303 - 13{,}326 = 393{,}977$. This amount of samples analyzed by us belongs to the last 13.2 years of the C-H project.

A value around 0 of the $\frac{\Delta\phi}{\Delta t}$ means a tiny modification of the direction per unit of time. Such cases Ire at the beginning of the project (see values before 2005 in Figure 3.14a). Starting with the SOI event, the angle of the consecutive samplings of the velocity direction modifies in a higher range per unit of time. The spacecraft trajectory was modified several times, but no detailed information is available publicly about these events. The accessible database of the NASA with 116 volumes contains samplings with high dispersion of the time. Values of the $\frac{\Delta\phi}{\Delta t}$ in the scale of over 1 rad/sec Ire sampled in case of relatively short delay time between consecutive samplings. The distribution of the $\frac{\Delta\phi}{\Delta t}$ is exponential conform to the histogram of Figure 3.14b.



(a)



(b)

Figure 3. 14: Cassini consecutive velocity vectors angle modification

The movement's direction is changing just in a small range for most samplings, but there are cases when the direction changes more radically. Analysis of the Cassini trajectories is a complex and time-consuming aspect that needs a high level of skill.

Modification of the Acceleration Vector Magnitude

Modification of the trajectory is made when the magnitude of velocity vector v (v_x, v_y, v_z) modify by a greater value than the threshold Th_v during the consecutive samplings. Calculation of the modification magnitude per unit of time of the velocity vector between two consecutive samplings (being the acceleration) is based on the velocity components given on the NASA database conform to the following relations:

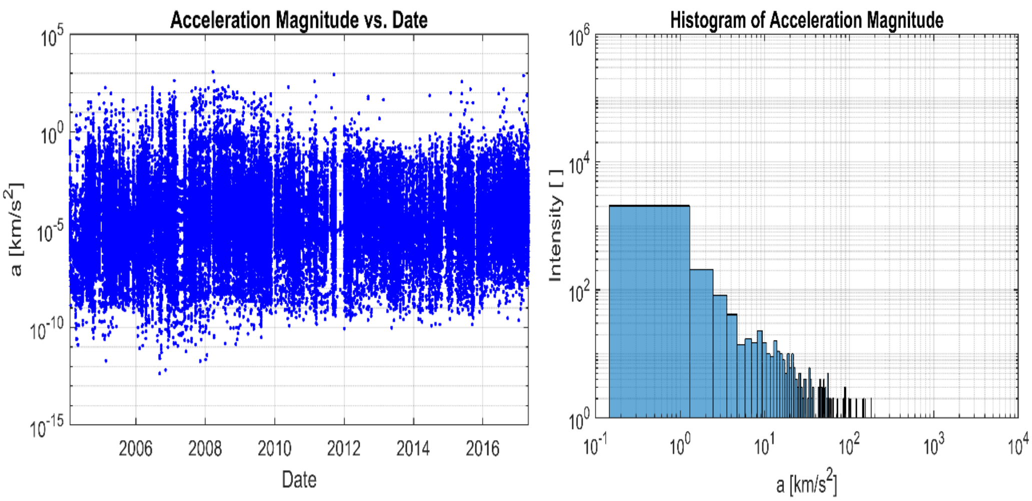
$$\bar{v} = \overline{v_x} + \overline{v_y} + \overline{v_z} \tag{3.17}$$

$$a_i = \frac{\|\overline{\Delta v_i}\|}{\Delta t_i} = \frac{\|\overline{v_{i+1}} - \overline{v_i}\|}{t_{i+1} - t_i}, \quad i = 1,2, \dots, N-1. \tag{3.18}$$

The magnitude of velocity modification can be derived using the following relation:

$$\|\overline{v_{i+1}} - \overline{v_i}\|^2 = (\Delta v_{x,i})^2 + (\Delta v_{y,i})^2 + (\Delta v_{z,i})^2 \tag{3.19}$$

where $\Delta v_{x,i}$, $\Delta v_{y,i}$, $\Delta v_{z,i}$ are the modification of the orthogonal velocity components in the sampling interval i, and $i+1$. The acceleration magnitude Cassini can be seen in Figure 3.15a.



(a) ***(b)***

Figure 3. 15: Acceleration magnitude of the Cassini (a) and related histogram (b)

It can be observed that the distribution of the acceleration magnitude is the power function conforms to the histogram of Figure 3-15b. The histogram denotes a method in which the intensity of acceleration events gauged within a particular magnitude period is distributed throughout potential magnitude values. Every level within the generated histogram expresses the rate of acceleration counts taking place among the acceleration span. The log-log scale histogram can be approximated by a linear function, a resulting power function dependence of the histogram for acceleration. Acceleration denotes a velocity change, either transmogrification within direction or speed or the two of them. At the time, there is a change in the speed, then the force of inertial is orientated ahead (in case there is a decrease in speed) or rearward (in case there is an increase in speed). While during the time that there is a change in the direction, then with this case, the force of inertial is oriented in the direction to left (in the case of right rotation) or in the direction to right (in the case of left rotation). It is obvious that the majority of the magnitudes of $\boldsymbol{a}$ are less than 1 km/s2.

Complex Event Detection of the Cassini Orbiter Trajectory

The main aim behind applying our classifier is to specify complex events from sensory generated data. To detect temporal semantics for complex event recognition, I prolonged the time index of the sensory data. Potential complex events of the data set are in the moment of change of observation sequences. Let have the indexes of trajectory modification where special events given by set I:

$$I_\phi = \left\{1 < i < N-1 \middle| \frac{\Delta\phi_i}{\Delta t_i} \geq Th_\phi \right\} \quad (3.20)$$

$$I_a = \{1 < i < N-1 |\, a_i \geq Th_a\} \quad (3.21)$$

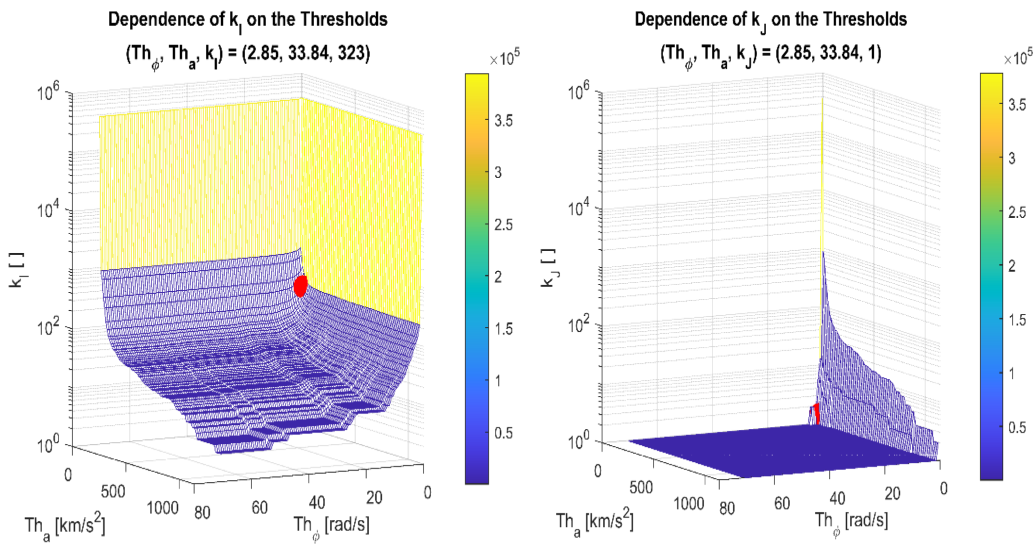
$$I = I_\phi \cup I_a \quad (3.22)$$

$$J = I_\phi \cap I_a \quad (3.23)$$

where I_ϕ and I_a are sample indexes of the analyzed NASA database for which the velocity direction modifications or the acceleration magnitude are greater than the corresponding threshold values. Set J is used to sense the individual effect simultaneously of the two conditions mentioned in the two previous subsections, if the cardinality of the set J is high, then these two conditions are not strongly dependent and help to detect complex events on the trajectory. The resulting set I contains all the sampling indexes detected by the proposed complex event detector.

$$I = \{i_1, i_2, \ldots, i_k\} \quad (3.24)$$

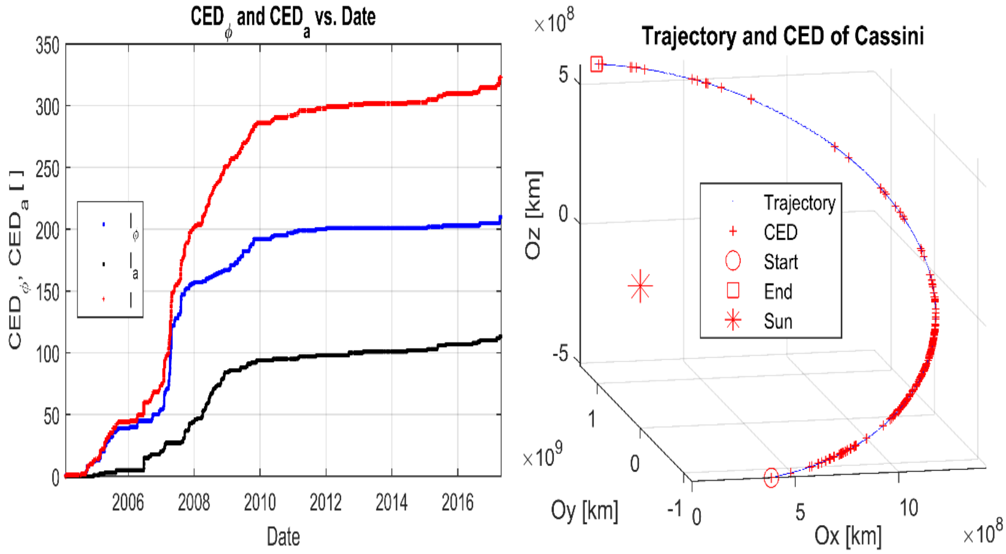
After the process of SOI in 2004, the spacecraft was executing several modifications of the trajectory conform to the commands sent by the supervisor team from the Earth. Cardinality k_I and k_J of the sets I and J, respectively, give the number of extreme events considered trajectory modifications of the Cassini based on the conditions (3.25) or (3.36) during the analyzed last 13.5 years of the project. The trajectory modifications executed should be less than the number of observations mentioned in section 3, $M = 10{,}851$. Based on table 3-13 and table 3-14. the number of executed maneuvers was considered to be 323. By exploiting dependency of the number of extreme values on the threshold values Th_ϕ and Th_a within our model, I can determine the working point in three-dimensional space Figure 3.16 sets out this dependency as a surface plot. The working point on both surfaces is placed on ordinates with extreme modification of the surfaces. To fulfill the total number of trajectory maneuvers, the values of the thresholds are$(Th_\phi, Th_a) = (2.85\ rad/s,\ 33.84\ km/s^2)$. For these threshold values, the cardinality of the set I and J were found to be $(k_I, k_J) = (323{,}1)$.



(a) (b)

Figure 3. 16: Cardinality dependence of sets I (a) and J (b) on the thresholds Th_ϕ and Th_a

The representation of complex events detected in the set I_ϕ and I_a are given in Figure 3.16a. The total number of extreme events based on velocity vector modification and acceleration magnitude modification is 210 and 114. The working points are represented with red bubble objects and are placed in the extreme modification points of the gradient of the surfaces.



(a) *(b)*

Figure 3. 17: Complex events of Cassini trajectory (a) vs. date. CEDs physical position (b)

It can be assumed that approximately two times more extreme events appear in the set I_{ϕ} than in set I_a. The majority of the trajectory maneuvers Ire executed in the Prime mission, and a relatively small number of modifications Ire done in the last, Solstice mission. The cardinality of sets I_{ϕ} and I_a in the function of time (Figure 3.17a) have a ratio of approximately 2/1. The positions of the CO during the trajectory modifications are represented in Figure 3.17b.

The spacecraft position in the solar system shows that majority of maneuvers Ire executed in the first mission (Prime). The Sun, the first sample, and the last sample are marked with a star, circle, and square characters, respectively. These two sets are not disjunctive because, in several samples, both conditions (4.25) and (4.26) fulfill. The union of these two sets gives precisely the number of 323 extreme events of the trajectory modifications. In continuation, I show the method to detect these trajectory maneuvers with supervised Recurrent Neural Networks (RNN).

3.6.3. Artificial Intelligence for Detection of Spacecraft Trajectory Modifications

The aspect of acquirements with ML indicates the aptitude of an algorithm to notice and memorize patterns among data to ameliorate the results, i.e., to utilize the existing data so that I can foretell events and solve the ambiguity. AI already has an implementation in many fields such as aviation, speech recognition, classification, et cetera [124]. The technology is foreseeable to consolidate future outer space exploration since it could process big datasets volumes, detect patterns in image datasets, and specify spaceship status. AI has become an effective method to find an answer to change detect or CED. ML can control spacecraft regarding handling geometric positions within a relatively low timeframe. Just as space missions are ever more frequent, intricate, and spacecraft to be sent away distance from Earth, there shall be an increasing request for rapid and automatic-adjusting machine-learning established navigation potency. The scope may comprise orbit adjustment and self-directed navigation. I developed an RNN and trained it to find such events based on CED. Embedding layers of the neural network are exploited to include vectors, which have a high point or dimensionality level. The LSTM layer passes the embedding layer as input and offers a greater abstraction scope for each data object. The memory gating method established in LSTM has turned the RNN into a robust mechanism to encode and seize long-term dependency. The stacked approach of LSTM can be considered an expansion of the LSTM model, having numerous hidden layers in which every recurrent layer includes several memory cells. The aim of utilizing multiple layers of LSTM is to impart more innovative data allocations [125].

3.7. Parameters of the Models

Deep neural network analysis involves the optimization of a complex function that provides input and an expected outcome. The models have several components, such as the values of max training epochs, initial learning rate, gradient decay factor, gradient threshold, etc. Table 3.10 lists various related hyperparameters. The network itself cannot choose the optimum values of these parameters to be defined and remedied until the network facilitates realistic forecasts to take advantage of its architecture and data collection.

Table 3. 10: Training option values of the RNN

Option	Value
GradientDecayFactor	0.9000
SquaredGradientDecayFactor	0.9990
InitialLearnRate	0.0200
GradientThreshold	1
MaxEpochs	100
Number of Classes	2

These parameters are commonly considered neural network hyperparameters. Various hyperparameters regulate multiple aspects of the neural network architecture. The hyper-parameters spectrum is also driven by research hypotheses that warrant the model performs well with unseen information during the testing period (see research hypotheses, section 1.4). A neural network has several hyper-parameters; turning all of them to their optimum value for the defined problem is one of the most challenging tasks in DL. Manual implementation takes much time and is unreliable, so automating the search method is essential.Usually, each layer between neural network input and output is called hidden layers. The number of hidden layers and the number of units in each layer defines network depth. They thus directly equate with the sophistication and computing complexity of the model. Numerous hidden layers with several units build a dynamic, large network. These large networks are hard to train successfully and need comprehensive testing samples. Immense networks may learn trivial sample knowledge, leading to an excessively Ill-fitted model. In large grids, background spreading is always slow, as many weights must be modified. As gradients flow across an intense network, they either extend and explode enormously, rendering the model unstable. Or over-degrade and vanish, causing a loss of usable information, and no learning becomes possible.

On the other hand, less hidden layers with inadequate units construct a shallow network and under-fit framework. Under-fitting is the opposite of over-fitting the neural network, where the network is too simplified that it is difficult to predict the underlying problem correctly. It is important to calibrate certain hyper-parameters for a reasonable number of hidden layers and units therein. A single training cycle (epoch) is completed before the entire batch of samples (Xtrain number of samples) from the training set is transferred through the network. These data samples also travel all over the network during learning. The number of epochs to learn counts on the network's size, the associated complexity, and the type and amount of training samples. Training epoch number also solves the under-/over-fitting problems of the model. Training a minimum amount of epochs is not enough to update all weights to their optimum values – under-fitting networks. On the other hand, programming for large numbers of epochs allows the algorithm to match the training data so perfectly that it performs poorly in unknown data – network overfitting. Weights are updated at each update step of the stochastic learning process, using an average number of samples from the training set [126]. This tiny batch is called a mini-batch. A preparation epoch involves many mini-batches. Mini-batch sizing also addresses over-fitting. When the mini-batch size is big, weights are adjusted after evaluating so many samples from the training data to accommodate them better – model overfitting. Too limited a mini-batch scale results in slow weights updating per epoch. Furthermore, if weights are modified too often without adequate instances, convergence to local minimum results in a significant error. Models are practiced in mini-batch sizes from 32 to 512, doubling each scale. The full CEC is reached at 256 mini-batch size.

In this research, Adam, the first-order stochastic optimization algorithm centered on gradients introduced in 2014, is used as an optimization function. The algorithm calculates the gradient exponentially. Averages are equations of the gradient's first μ moment and second (uncentered variance). Using these, the algorithm calculates adaptive learning levels for different weights. Parameters β1 and β2 control the decline of these moving averages [127].

3.7.1. Architecture of Elaborated LSTM

LSTM is a special neural network (RNN) architecture developed to model temporal sequences. Long-range LSTM dependencies allow LSTM more efficient than conventional RNNs. Compared to RNN, LSTM has specific units known as hidden memory blocks. Memory blocks contain self-connected memory cells carrying the network's temporal state and special multiplicative units called gates to control knowledge flow. Each memory block in the original design contained three gate forms:

- Input gate: this gate regulates input activation flow through the memory cell.
- Output gate: this gate regulates the output flow of cell activations to the remainder of the network.
- Forget gate: scale the cell's internal state before inserting it into its self-recurring link, thereby adaptively ignoring or redetermining cell memory.

The current LSTM architecture includes peephole connections from its internal cells to the same cell gates for correct performance timing. The LSTM architecture is always unfolded over the τ(time) axis to make interpretation simpler, represented by the following diagram (see Figure 3.18). It can be shown from the diagram that each LSTM block gets the following signals: input signal (x), input gate (i), recurrent (h) and forget gate signal (f), and output gate signal (o). The following diagram can represent the flow of the process in each LSTM memory block. A projection from inputs $x = (x_1, \dots \dots x_T)$ to outputs $y = (y_1, \dots \dots y_T)$ can be computed on the LSTM network by evaluating the activations iteratively from network unit t = 1 to T. This can be illustrated in the consequent formulas. Several gates organize the flow of the related information in the cell of LSTM. In the beginning, there is the forget gate that determines which must be kept or discarded. Information originated from the preceding hidden state. Also, the information comes from the present input, which is pushed to the sigmoid function; at this stage, the values appear to be among 0 and 1. If the value is nearby 0, this denotes forget, and if it is nearby 1, it denotes keep. The forget gate's operation can be illustrated by the mathematical equation number (3.25).

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \tag{3.25}$$

To bring up to date information to the cell state, the input gate, where the former hidden state beside the present input is passed to the sigmoid function, determines values to bring up to date via transmuting the values to settle down among 0 and 1. Wheresoever 0 implies not influential, while 1 implies influential. There is a need to go by the hidden state and the present input towards the tanh function to squelch the values among -1 and 1 so that I can control and adjust the network. The next step is to multiply the tanh product with the product of the sigmoid. This output of sigmoid can determines which information is necessary to retain from the results that came from the tanh. I must have sufficient information to compute the cell state, which obtains pointwise multiplication operation by the vector of forgetting.

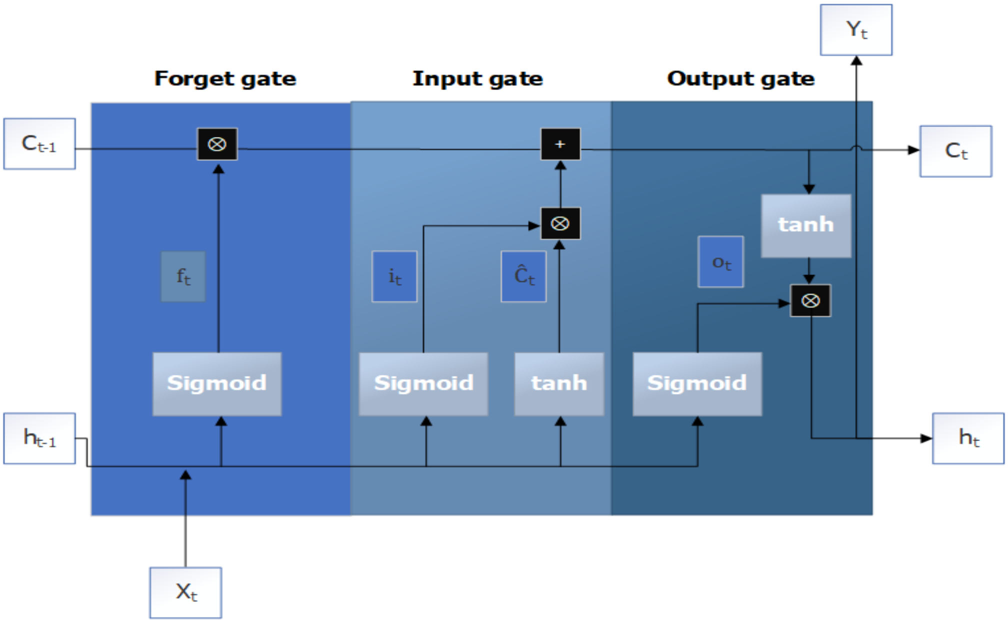


Figure 3. 18: Overview of LSTM cell

This holds a probability of diminishing values inside the cell state in the case it receives multiplication by values close to 0. There is a necessity to get the resulted output of the input gate and perform cell state update by pointwise addition, which produces a newfangled value in which the network considers pertinent. This process provides us with a freshly updated state for the cell. The input gate's operation can be represented by the mathematical equation numbers (3.26) and (3.27).

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \tag{3.26}$$

$$\hat{C}_t = \tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \tag{3.27}$$

Finally, the output gate determines what must be the following hidden state, which includes the former input information, besides it is utilized for prediction. The output gate's operation can be stated by the mathematical equation numbers (3.28) and (3.29).

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{3.28}$$

$$h_t = o_t * \tanh(C_t) \tag{3.29}$$

while the current cell state can be mathematically characterized by the equation number (3.30).

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \tag{3.30}$$

however, the operation of update operation can be provided by equation number (3.31).

$$u_t = \tanh(W_{xu} * x_t + W_{hu} * h_{t-1} + b_u) \tag{3.31}$$

where: Wi, Wz, Wf, Wo, Ui, Uz, Uf, Uo are the parameters that are to be calculated at the model training phase. σ (sigmoid) and tanh are functions for activation, while the biases are b's, which are calculated during training, while (.) represent pointwise multiplication. As shown in Figure 3.18, the LSTM various operations. First of all, the former hidden state is passed along the sigmoid activation with the current existing input. Afterward, the recently updated cell state goes over the tanh function. Then the output of tanh is multiplied with the output of sigmoid so that a judgment can be made now on what information the hidden state must hold. The activation Function is a linear combination of input and weights calculates the output in the neural network layer. In certain situations, the associated issue is complex, and a linear system cannot actually model it. This is accomplished by calculating the layer's output by a non-linear function, generally called an activation function. There is plenty of activation features. The following are the different forms and their composition:

Hyperbolic tangent Equation:

$$\tanh(x) = \frac{2}{1+e^{-2x}} - 1 = 2 \cdot Sigmoid(2x) - 1 \tag{3.32}$$

Softmax Equation:

$$Softmax(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{i} e^{y_j}} \tag{3.33}$$

Sigmoid Equation:

$$Sigmoid(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{1+e^x} \tag{3.34}$$

The activation function of a layer depends on its input range and goal output. ReLu function supports smooth gradient flow; it is used over time in all dense layers. However, the ReLu feature does not bind positive values; therefore, repetitive activation rises exponentially when put in a repeated layer, causing network instability; computational methods detect this behavior. Tanh is then used to trigger forward signals, and Sigmoid is used in repetitive signals from each repeating layer in both model architectures. The basic theory in regression is to disfigure the input by the hidden layers in a non-linear manner such that linear separation is possible in the output layer while using a linear activation function in the output layer.

Chapter 4: Analysis Process

This chapter discusses the analysis methodology. The strategies utilized in interpreting the data are described. It explains taken study measures to evaluate a study issue and the rationale for the use of particular methods or strategies used to define, process, and examine knowledge applied to understanding the problem. The purpose of this chapter is to include a concise and complete explanation of the followed analysis steps.

4.1. Analysis Models of the Generic Environmental Data

4.1.1. Healthy Residential District Data Analysis

The evaluation process involves special statistical procedures, including loading the collected data, generating a 3D GIS map, data analysis of the 3D map of the CO_2 emission level, and then the region identification process. The generated Figure 4.1. provides the bihistogram illustration of sampling coordinates XY, where X illustrates longitude and Y illustrates altitude.

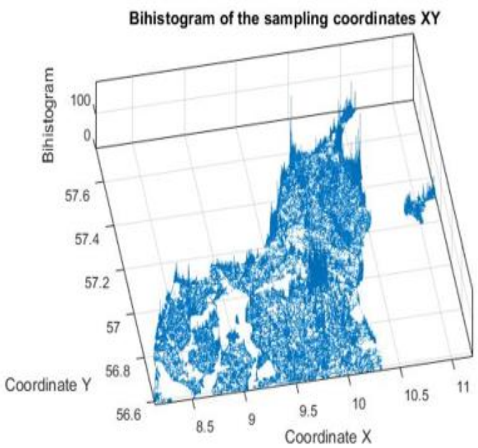


Figure 4. 1: Sampling coordinates bihistogram

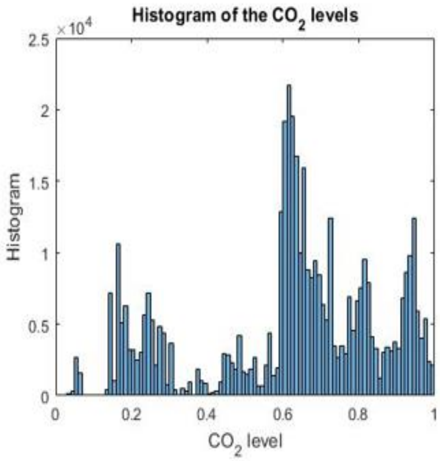


Figure 4. 2: Histogram of the CO2 level

It can be seen that the sampling intensity is not homogeneous in the territory. This phenomenon is caused by the specialty of the sampling process of the CO_2 levels by sensors installed on the 150 moving cars. In the biggest town, Aalborg, the measurements are the most intensive in time. Figure 4.2 displays the histogram of the CO_2 emission concentration in the analyzed territory. The majority of the CO_2 level samplings Ire 60%...70% of the maximum CO_2 level. It is important to notice that a low number of samples Ire with relative CO_2 level in the 30%...40% range. Among the possible method to record the sampling, the latitude is to utilize the Probability Distribution Function (PDF) as a function over values of any sets or attribute it as the Cumulative Distribution Function (CDF). The resulting histogram is shown in Figure 4.3.

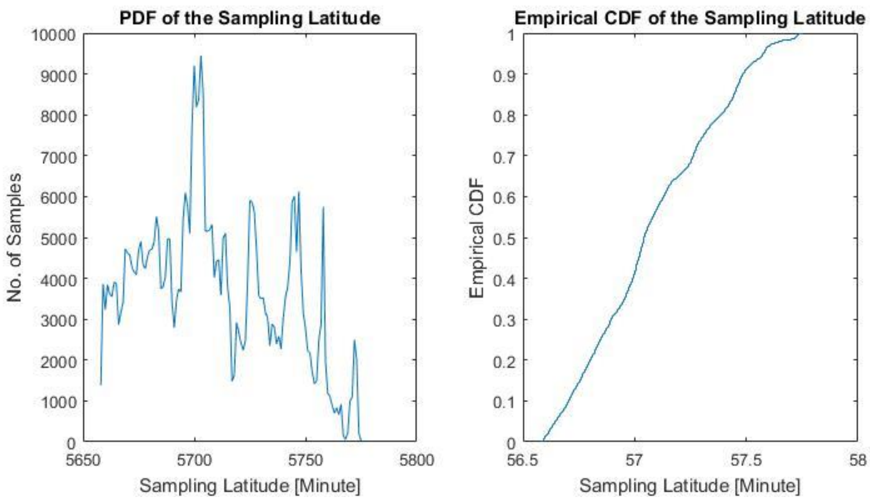


Figure 4. 3: Probability distribution function and Cumulative distribution function of sampling latitude

The non-uniformity of the longitude and latitude sampling coordinates is caused by the presence of the sea territories of the analyzed peninsula. To characterize the likelihood of CO_2 level dependence on altitude with (Z) coordinate Figure 4.4 is provided.

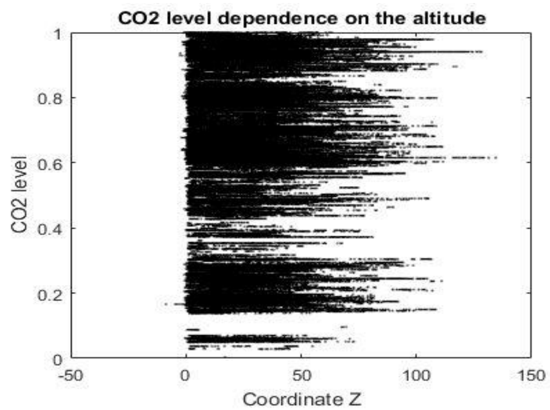


Figure 4. 4: CO2 level dependence on the altitude

The CO_2 level decreases as the altitude increases. It is worth mentioning that the emission level is related to the altitude of the land above or under the sea level, where the samples have been collected, as the highest point is 30 m above the sea level and the lowest point is around 7 m below the sea level.

4.1.2. Climate Comfort Detection Approach Analysis

Here I'm concerned with the rank associated with raining, radiation of sunshine and wind, then to determine the TCI by using formula number 3-1. Finally, specifying the tourism climate numerical quantity and its associated category by using Table 4.1. Time series algorithms contain a concatenation of data explicit points detached orderly in time. The term time series is being directed to inspect advancement towards TCI. Usually, in such types of algorithms, the data has to be homogenous. I adopt a huge weather data set of Jordan for a long time (1901-2017). The µ temperature for every month has been computed.

Table 4. 1: TCI numerical quantity and associated category [91]

Amount related to comfort of TCI	*Rank*	*Rank state description*
90-100	9	Ideal
80-90	8	Excellent
70-80	7	Very Good
60-70	6	Good
50-60	5	Acceptable
40-50	4	Marginal
30-40	3	Undesirable
20-30	2	Very Undesirable
10-20	1	Extreme Undesirable
0-10	0	Impossible

TCI was computed using the selected data set for the period of January -2011 till May -2018 for all the three previously mentioned stations. In this study, I utilized Jordan's monthly climatic data from 1901 – 2017 to review the average temperatures and precipitation to conduct the needed analysis to specify the TCI values for every single month via a more sophisticated data set for the last six and half years. I'm providing a multiscale TCI, which can be considered as prognostic, that contains a three-time window scale (7 days, 10 days, and 30 days), so by this multiscale an early short term and long-term prognostic TCI values are provided, that is suitable for the accordance tourist planned to stay period in Jordan. The approach used to address the missing data stations is comprised of an automated accuracy control and statistical amendment method, only those wrong data, and inhomogeneities falling outside introduced limits would be specified and conveniently addressed, there was periodically missing data, this can be seen in Figure 4.5 which may represent a value that was not recorded by the sensor, but it will affect the final results of the research it has not been included in the calculation process. The approach of time series the algorithm was formerly utilized in such researches. The Artificial Neural Network (ANN) method provides a pounce forward in computational multilaterally.

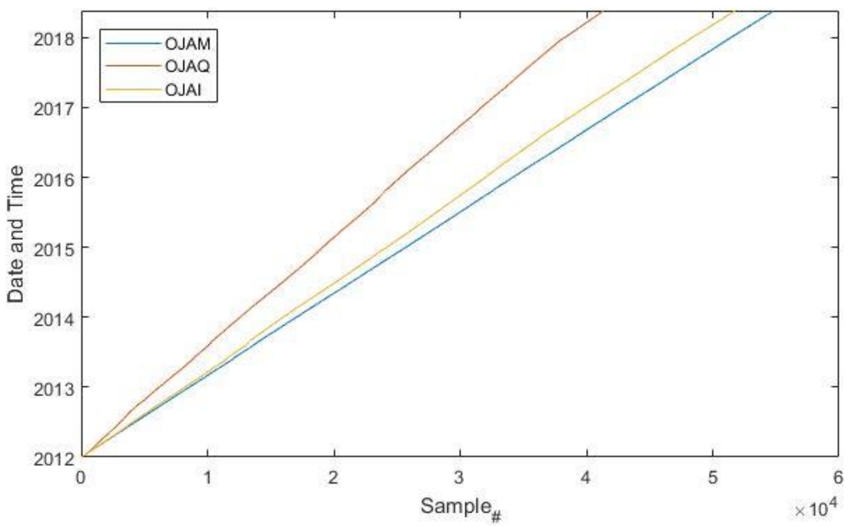


Figure 4. 5: Sampling over last 6.5 years

The technique has the merit that it empowers input of a huge number of variables concurrently, the adopted technique within the ANN that I will use in our research is the backpropagation technique, in which I have split it into two stages: propagation and weight assigning.

Stage One: Propagation

Every propagation includes the following phases: Initially Forward propagation of the associated training patterns input is provided via the neural network to produce the activations of the propagation's output. Then Back propagation of the output of the activations of the associated neurons propagation over the neural network by utilizing the training patterns entity target to produce the deltas of the whole output neurons and hidden neurons.

Stage Two: Updating the Weight

A function of sigmoidal activation is multiplied with the input and output to acquire the weight gradient, then to add the avoirdupois rate of the gradient to the weight. Among the characteristics, 5 input nodes contain the 5 TCI formula components, with one hidden layer and one output node. There is no restricted regulation as to how many neurons or layers. However, a single hidden layer is considered adequate. Neurons number associated with the hidden layer ought to be in the midst of the input and output layer's size, which is, in our case, two neurons based on the data suitability. By sure, the output layer has an individual output as I'm performing regression.

4.2. Analysis of the Structured Prediction Method Based on Revealing Event Complexity

CEP has been promoted into a more effective pattern of preference for supervising the evolution implementation. Also, it has a vigorous effect on the information framework. Moreover, it is a quite spirited research field. Figure 4.6 provides a proposed filtering model for detecting a complex event. It is assigned a feature vector as a special event for every window frame, which will be detected based on the magnitude of the window slider magnitude.

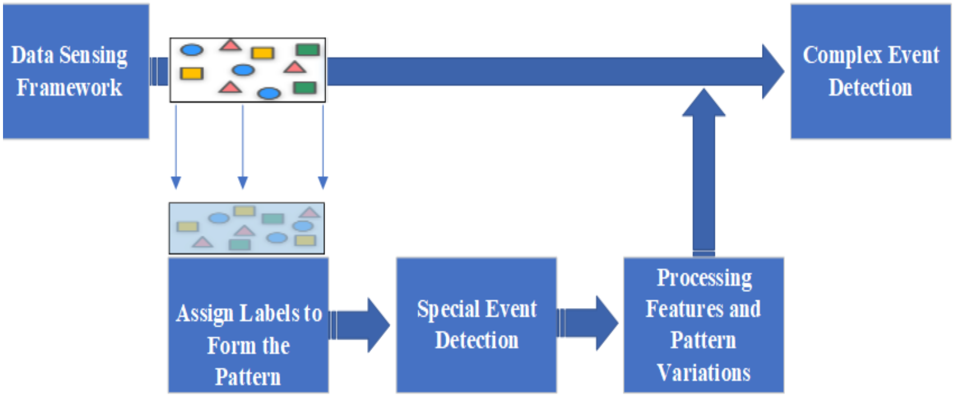


Figure 4. 6: Filtering model of the complex event detection

These vectors will be linked together in a chain to generate a distinctive special event vector (for t=1, ..., t_n). The event is termed as a special event by using a set of categorizations, which are put at the starting and ending points of each set of consecutive time intervals $[t_i, +t_{i+1}, \ldots\ldots t_n]$. The existence of adequate veracious data is assessed as an initial phase to detect if the change is due to an extreme event (set of special events) and make sure that there is no malfunction in the camera that is taking the images if these predefined benchmarks are met. A second phase is carried out to analyze these benchmarks to detect complex events or events. Pattern categorization is the task of allocating a category label to an event or object, the allocation is counting on criteria and the sampling acquired from the event.

The sampling process is made obtainable by the sensory framework. An extreme event indicates those situations that are quite situated at a great distance in space or time from the principle that they are normal to be categorized as unique. The extreme event depends on the significance of a magnitude of a set of special events, the significance of a special event could be determined depending on the threshold(max-limit) that can be followed via various labels that characterize particular patterns such as packets sending start and end time. As a result, it is useful to exploit features expediency for representing the event frame. Given a time interval T which has events vectors N, i.e., $\{T_n\}_n^N = 1$, the objective is to reveal the score of event complexity via our proposed method. I break down each time interval Tn into multiple smaller intervals that contain a number of taken images $\{Ph_i^n\}i = 1^{nk}$, where nk points out the number of events in the k-th interval by adopting the splendid constructed CED approach. By utilizing the approach of CED (with the optimal frame), each time interval Tn will be divided into several smaller intervals based on the presence of specific observation in the time interval and the image. The time interval size might influence the performance; however, it is not a trouble with our work scope since the size of the interval generated by the image event detection algorithm is stationary (the related algorithm is provided below).

Aggregating all images events in the time interval drives to $\{Ph_i\}_i^N = 1$ where $N = \sum_{k=1}^{K} n_k$. Then, I calculate the wCEL for each time interval, which leads to transforming the observed data into stunning detected events. After that, the event complexity is revealed without additional reasoning, as it has a great consistency to represent the event complexity and features. The below meta-code script shows the algorithm of revealing detect event complexity.

Meta-Code Script 4.1: Algorithm of Revealing Detected Event Complexity

```
Input: stream of vector {T_n}_n = 1^N, wCEL to each time interval

Output: reveal event complexity

for n = 1, ..., n - 1
      Repeat for each training example
       Training to improve L_t using D_t, o
       perform
              Extract detected events {Ph_i}_i^N = 1
              Extract features
              Calculate the wCEL
              Update Iights of wCEL by (aggregate) data
              until complexity revealed
print (revealed output)
```

4.3. Variables Analysis for Special Event Detection and Weighted Complex Event Level

To this end, LSTMs are indeed capable of providing reliable forecasting variables and temporal scale perception. The arrangement of the evaluation process has been positioned according to the group's sequence below:

4.3.1. Timing Variables (Group A)

The previously mentioned timing group contains the time moments for the images that include the μ, starting, and ending capture time of the sample at the Cassini and the starting and ending time of the sample at the Earth. Figure 4.7 expounds the sampling moments among time intervals. Figure 4.8 shows the number of samples in each year of the project.

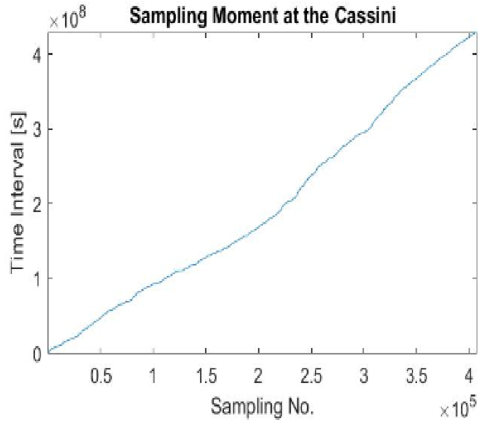


Figure 4. 7: Sampling time vs. sampling ID

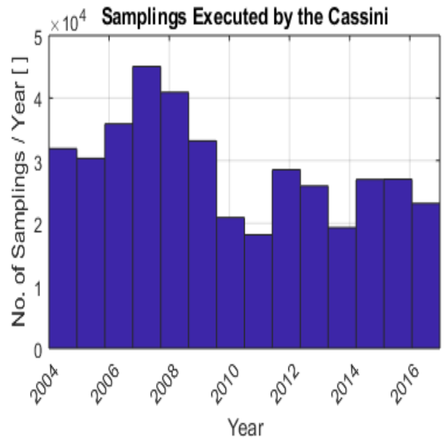


Figure 4. 8: Number of samples per year

It should be mentioned that the inhomogeneity of the sampling intervals producing a nonlinear curve in Figure 4.7. The majority of the samplings were captured in the first half of the expedition, and a smaller number of capturing was done in the seven-year-long phase named Extended-Extended Mission.

4.3.2. Temperature Variables (Group B)

The ISS cameras were built to retain their concentration without relocating components by careful instrument temperature regulation. Camera temperature sensors are attached directly and sub-system controlled.

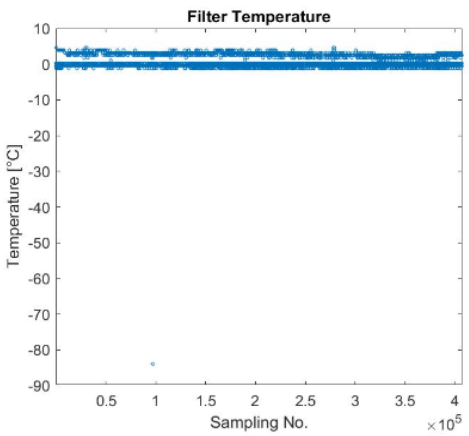


Figure 4. 9: Filter temperature over sampling

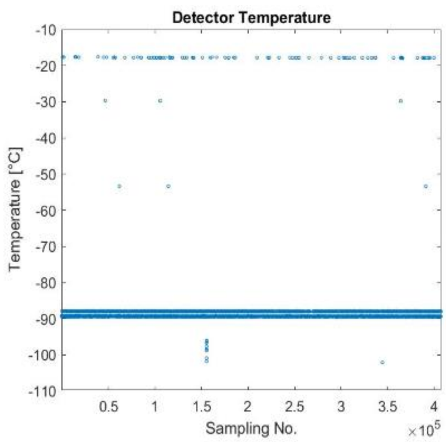


Figure 4. 10: Detector temperature over sampling

The temperature of 5 metadata variables is analyzed (filter temperature, detector temperature, front and rear optic temperature, sensor head electronics temperature), the filter temperature indicates the actual temperature of the filter wheels, the detector's working temperature, roughly -90°C, is adequate to ensure very low dull current build-up even at the peak exposure periods. While the optimal operating temperature spans between 0 to 10 °C for both the narrow-angle camera and the wide-angle camera. (Figure 4. 9and Figure 4.10) shows the filter and detector temperatures over sampling. Throughout the flight mission, the devices, excluding the detector (-90 °C approximately), shall not experience temperatures higher than +35 °C or lower than -25 °C. The average temperature variation will not transcend the average of 8 °C per hour. Regarding the detector, the operating temperature is required to repress the dim current and reduce the neutron and gamma proton emission impact.

4.3.3. Communication Variables (Group C)

The communication group has four labels (expected packets, received packets, instrument data rate, instrument compression ratio). The label of the expected packets demonstrates the gross number of expected packets that will be stored on the spacecraft solid-state recorder for each image. To transform to volume measured in bits, I need to multiply the expected packet's value by 7616 bits per packet. The concept of received packets signifies the veritable packet number received from the spacecraft solid-state recorder for each image, both of these keywords are given in (see Figure 4.11).

The instrument data rate label is measured by (kilobits/second), and it represents the data rate that the data was transferred out; it has five modes; the lowest rate is 60.9 Kbits/sec, and the highest is 356.6 Kbits/sec. The data rate can also be expressed by packet/sec with 8 as the lowest rate followed by 16, 24, 32, and 48 as the highest.

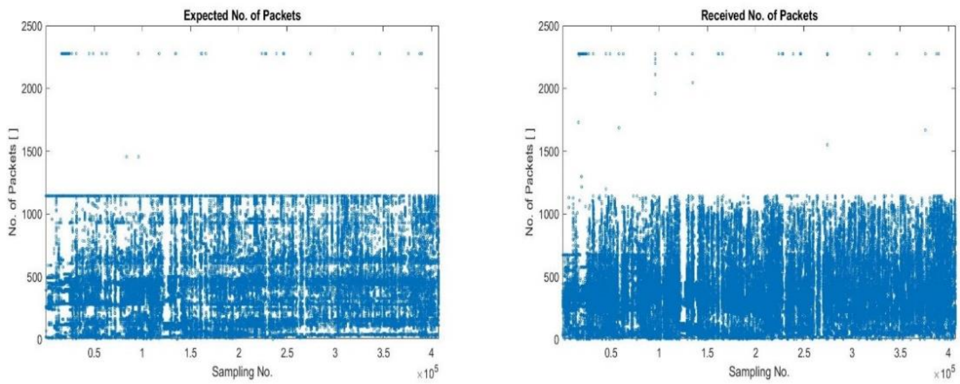


Figure 4. 11: Rate of the expected and received number of packets

4.4. Analysis of CKE Approach

More often than not, features such as edge or lines are considered as a primary descriptor that can be easily indicated without executing any complex procedures, which is recognized as (bottom-level) or common features that are generally designated to those nonexclusive features which may be directly observed from any displayed image, such as surface or line merit. Lineaments categorized as a high-level indicate the features vectors gotten from bottom-level merits via utilizing affirmed advanced approaches. Figure 3-6 provides a proposed filtering model for detecting a complex event. This algorithm identifies special events of the multivariate time series. I constituted the event detection process as following, let

$$\Omega = \{\mathrm{v_1, v_2, \dots, v_k, t}\} \tag{4.1}$$

be the space of events, where $v_i, i = 1, \dots, k$ are k independent variables, and t represents the time. Accordingly, I inspect discrete points in time (moments) of the process of sampling, denoting variable t to be classed to the finite time set S:

$$S = \{0 = t[0] < t[1], \dots, t[n-1] = T\},\ n\epsilon\mathbb{N}^* \tag{4.2}$$

I defined the time interval among the analyzed dataset with a distinct measure such that $\Delta t[m,r] = \left[t\left[m - \left\lfloor\frac{r}{2}\right\rfloor\right], t\left[m + \left\lfloor\frac{r}{2}\right\rfloor\right]\right] \subset [0,T]$, where $m, r\epsilon\mathbb{N}^*$ are middle index and number of samples in the underlying time interval, respectively. Parameter r is used as the memory size of the CKE model. The number of outliers $O_i[m,r]$ for variable v_i in time moment $t[m]$ and memory size r is the cardinality of the set $V_i[m,r]$ given by the formula below:

$$V_i[m,r] = \{v_i[j] | \frac{\left|(v_i[j] - \overline{v_i[m,r]}\right|}{\sigma_i[m,r]} \geq \rho\}, \tag{4.3}$$

where $\overline{v_i[m,r]}$ and $\sigma_i[m,r]$ are moving average and local σ of the variable v_i, respectively in time interval $\Delta t[m,r]$ and $j = m - \left\lfloor\frac{r}{2}\right\rfloor, \dots,\ m + \left\lfloor\frac{r}{2}\right\rfloor$. ρ represents the outlier detector sensitivity, and it is specified via the acquisition of knowledge (learning process). The outlier searching method in formula (4-3) uses the absolute standardized time series of variable v_i for each time interval $\Delta t[m,r]$. Severity function $f_{CKE}[m,r]$ of the space Ω in time moment $t[m]$ and memory size r are given by:

$$f_{CKE}[m,r] = 1 - \frac{1}{k}\sum_{i=0}^{k-1}\frac{O_i[m,r]}{r} \tag{4.4}$$

Values of severity function $f_{CKE}[m,r]$ belong to $[0,1]$ as in time interval $\Delta t[m,r]$ every variable owns at most r outliers. In that respect, there are k independent variables utilized in equation (4-4). The subset $S_{CKE} \subset S$ is named CKE set of space Ω and is given by the following formula:

$$S_{CKE} = \{t[m] \mid Th < f_{CKE}[m,r] < 1\}, \tag{4.5}$$

where Th is the severity threshold determined by the learning process and $m = 0, \dots, n$. Because of the positive and subunit range property of the severity function mentioned before possible range for the severity threshold Th is $(0,1]$. The higher is the Th, the stronger becomes the severity of the CKE method, and the lower number of events are identified as special events. Learning phase execution is required to determine the optimum values of parameters r, ρ, and Th before applying in practice this CKE analysis method. The hitting rate of the CKE method is the ratio of found SEP events (cardinality of S_{CKE}) and the total number of samples (n). The presented approach handout eminent results, I found that there is a need for an approach that guarantees knowledge representation with precis event reasoning.

4.5. Analysis of Meta-Learner LSTM Approach

There are several parameters of similarity which could be exploited within our approach. I consider the process of image classification by analyzing several parameters as a preprocessing phase for image classification and analyses of a block of tensors via LMR for image patches classification where these investigation processes passed into (LSTM) blocks. I'm using the LSTMs block unit to exploit the memory dependencies component to regulate the information flow; as I deal with a Bd meta-learning, LSTM is a perfect choice. The prime factor to DL's prosperity is its potentiality towards acquiring knowledge from hierarchical features via enormous amounts of raw data such as text or images. Extracted features through DL methods have been confirmed to be outstanding and better than traditional approaches in many different aspects, such as preciseness and reduced resource challenging.

4.5.1. Primary Algorithm of Meta-Learning Long-Short Term Memory

The learning algorithm will include an input, which aims to perform training via a training set referred to as $D_{train} = [(X_t, Y_t)]$. Also, it has an output with a parameter θ, which will model the learner (AT), the aim of the learning algorithm to gain a robust performance performed on the test set $D_{test}(X, Y)$. The below meta-code script provides the primary algorithm of meta-learning LSTM.

Meta-Code Script 4.2: Primary Algorithm of Meta-Learning LSTM

```
Input: task distribution P(T), labeled image big dataset
       Bd, learning rate R
Output: θ_D , θ_G , θ_M

while true: Initialize θ_D , θ_G , θ_M
     for task T = 1, 2... do
        calculate corresponding loss of meta-learning:
        LT (θ_M, θ_G);
        calculate corresponding loss of map-reducer
        discriminator (D): L(x, y) (θ_D, θ_G);
        (θ_G, θ_D, θ_M) - R∇ [J(LT(θ_M, θ_G), L_(X,Y) (θ_D, θ_G)] := θ_D , θ_G , θ_M ;
print(output)
```

4.5.2. Train of Meta-Learning Long-Short Term Memory Algorithm

The Meta-learning LSTM algorithm will include an input, which has an aim to perform training and testing via a meta-validation training set referred to as D meta-validation train-LTSM train = $[(\boldsymbol{D}_{\text{train}}, \boldsymbol{D}_{\text{test}})] = 1$; also it has an output with a parameter φ, which will model the Meta-learning LSTM algorithm; this process aims to gain a robust performance via the set of (Meta-Test) D Meta LSTM test= $(\boldsymbol{D}_{\text{train}}, \boldsymbol{D}_{\text{test}})$. The following meta-code script shows the Meta-learning LSTM training algorithm

Meta-Code Script 4.3: Meta-learning LSTM training algorithm

```
Input: task distribution P(T), labeled image Big dataset
(Bd), images batch size with n tasks, image batch size
with m instances, meta- learner LSTM with Initialization
Φ as a primary random parameter vector learner (AT)
accompanied by the parameter θ, meta-training set
(D_meta−train), meta-learner M accompanied by the parameter
φ.

Output: θ_D , θ_G , θ_M = {φ,r}
dataTrain = LOAD
dataTest = LOAD

for iterations = 1,n do
   haphazard dataset from D meta-train initialize φ,r,
    θ_D, θ_G := D_train , D_test
    splitting dataset to training and testing with a
    sequential model train and validate
    inaugurate learner parameter: = 0 := Cell
    Activation = sigmoid
    for every task T do
       random batch obtained from the training dataset
       (D_train):= X_t,Y_t
       obtain learner loss on train batch := …
       (AT (X_t; θ_t-1),Y_t):= L_t
       obtain meta-learner output := c_tM ((∇ θ_t-1 Lt, Lt); φ_d-1)
       c_t bring up to date learner parameters := θ_t
       D_test := X, Y
       obtain learner loss on test batch := L_test L (AT
       (X; θ_T), Y
       bring up to date meta-learner parameters := …
        update φ_d by utilizing(∇_θd−1 L_test)
print (output)
```

4.5.3. Feature Extraction and Labeling

Feature extraction depicts the affined shape details that comprised in recognition of a pattern, the concept of feature extraction considered as discriminatory kind of dimensionality reduction, where the purpose of the extraction process is to attain the significant pertinent data from the source of that data to appoint them in a minimized dimensionality. Referring to time or circumstance, the input data is so huge to be handled based on the followed set of rules in an algorithm, so input data should be metamorphosed into a minimized form of features. The process of metamorphosing input data into a group of features can be defined as feature extraction. The extraction process involves capturing essential details and distinctive characteristics from raw data, where each feature is exemplified through a feature vector that turns into its identity [128].

4.5.4. Map-Reduce Framework

MapReduce model contains two tasks; Map-task and Reduce task. MapReduce model is deduced from the function amalgamation of a map and reduces; this model is exceedingly utilized to process an enormous dataset. MapReduce uses the set of (key/value) as a data category [129]. A representation of the MapReduce framework is displayed in Figure 3.8. The significant stages of the MapReduce platform are Mapper, Reducer, and a middle phase known as shuffle, all of them are introduced in the following section:
Mapper function: handles input data and carry out a few calculations on that input, then generates intermediate outcomes with the arrangement of (key/value) [130]. Reducer function: a group of key values and averaged key, it mingles all values with each other to create values of a lower set [131]. Shuffle phase: within the MapReduce platform, after the task of the Map, ordinarily considerable volumes of middle data need to be shifted to reduce operation from the map operation; the shuffle moves the available data from the mapper to the reducer phase, after being arranged via the keys. Thus, the whole pairs with an identical key shall be organized and grouped with each other and then transferred [132]. MapReduce's framework carries out those functions side by side efficiently, even in many devices [133]. The Meta-LSTM could be considered as past learning of the semantic structure, and the pivotal LSTM is the subsequent knowledge. Consequently, the learned Meta-LSTM offers a competent method of implementing transfer learning.

4.6. Analysis of Spacecraft Trajectory Modifications Detection Approach

The aspect of acquirements with ML indicates the aptitude of an algorithm to notice and memorize patterns among data to ameliorate the results, i.e., to utilize the existing data so that I can foretell events and solve the ambiguity. AI already has an implementation in many fields such as aviation, speech recognition, classification, et cetera. The technology is foreseeable to consolidate future outer space exploration since it could process big datasets volumes, detect patterns in image datasets, and specify spaceship status. AI has become an effective method to find an answer to change detect or CED. ML can control spacecraft regarding handling geometric positions within a relatively low timeframe. Just as space missions are ever more frequent, intricate, and spacecraft to be sent away distance from Earth, there shall be an increasing request for rapid and automatic-adjusting machine-learning established navigation potency. The scope may comprise orbit adjustment and self-directed navigation. I developed an RNN and trained it to find such events based on CED. Embedding layers of the neural network are exploited to include vectors, which have a high point or dimensionality level. The LSTM layer passes the embedding layer as input and offers a greater abstraction scope for each data object. The memory gating method established in LSTM has turned the RNN into a robust mechanism to encode and seize long-term dependency. The stacked approach of LSTM can be considered an expansion of the LSTM model, having numerous hidden layers in which every recurrent layer includes several memory cells. The aim of utilizing multiple layers of LSTM is to impart more innovative data allocations.

4.6.1. DL Method of Detecting Trajectory Modifications

Based on the work provided in [111], how two or more concepts or objects are connected among the orbital elements would help analyze the impact on spacecraft trajectory. The efficient analysis of any framework entails the empirical observations reference in the time domain. The proposed approach is an amalgamated framework, which can specify trajectory modifications among the mission of the C-H expedition. It is a deep neural network based on Long Short-Term Memory. A significant benefit of DL networks is that they always develop as the data size grows. The analysis of trajectories allows acquiring information, not just about the spacecraft motion, but allows gaining a better motion analysis based on ML. The framework captures the trajectories as inputs and analyses them temporally and spatially, depending on the sample number and timing of that samples beside the spacecraft velocity. The input to the RNN system is a sequence of sample ID $i \in \{1, \dots, N-1 = 393{,}976\}$, sampling intervals $\Delta t_i = t_{i+1} - t_i$, modification of the position coordinates $(\Delta x_i, \Delta y_i, \Delta z_i)$ and modification of the velocity components $(\Delta v_{x,i}, \Delta v_{y,i}, \Delta v_{z,i})$ among the last 13.5 years of the studied time interval. The input of the neural network is a $7\ x\ N$ matrix X conforms to the formula below:

$$X = [X_1, X_2, \dots, X_{N-1}] \tag{4.6}$$

where the column vectors X_i have the following elements:

$$X_i = [\Delta t_i, \Delta x_i, \Delta y_i, \Delta z_i, \Delta v_{x,i}, \Delta v_{y,i}, \Delta v_{z,i}]^T \tag{4.7}$$

The data set having $N-1$ samples are divided into the subsets of objects conform to the training sets with size of (50%), validation (25%) and test (25%). The RNN system executes a binary classification of the trajectory samples. It is obvious that extreme events of the trajectory are time-dependent and can be detected based on the sequences of the sampled multidimensional time series. To keep the orbiter on the complex helicoid discussed earlier automatic modifications Ire executed by the orbiter. Figure 4.12 shows the used recurrent network.

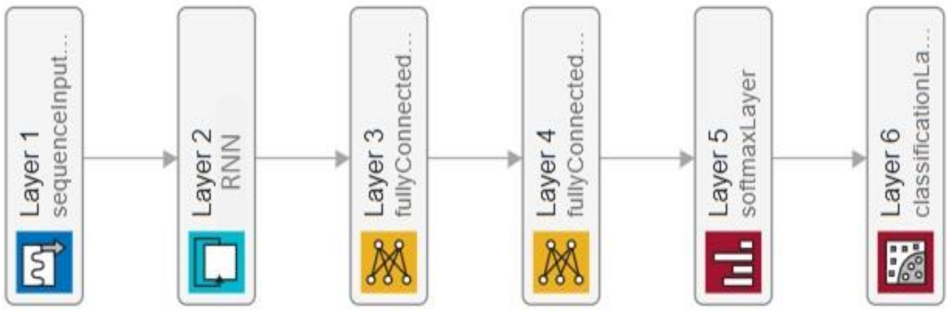


Figure 4. 12: The architecture of the adopted RNN

Because of different scientific and astronomical targets of the project, there Ire sent modification commands of the trajectory by the human control team from Earth. Usually, these targets involve orbiting an entity such as a comet, moon, or earth or landing the target object on the spacecraft (or the probe). For better sensing the memory behavior of the trajectory, I used LSTM layers of the neural network. On layer two LSTM, BiLSTM, and GRU RNNs have been used with different parameters. The output of the neural network system is a binary function indicating the appearance of the extreme modification of the CO trajectory. The algorithm type of neural network training is ADAM; the gradient threshold method is L2Norm. The number of classes is two because I use this network to detect the complex event of the trajectory. As the CED conditions (see relations 3-25, 3-26) are fulfilled for any trajectory samples, that sample is classified True, otherwise is classified False. The confusion matrix concerning binary classification is a 2×2 table intended to depict the classification model performance. It shows precisely the number of classified samples and in which class [134]. The matrix weighs up the similarity or dissimilarity among the values of the actual target and the predicted values by the used model. The confusion matrix has four variables listed below: True positive (TP) represents the outcome at which the model accurately predicts a positive category. The condition is accurately identified at the time that it present. True Negative (TN) gives the outcome at which the model accurately predicts the negative category. The condition is not discovered when truant. False-positive (FP) represents the outcome at which the model inaccurately predicts a positive category. The condition is located without being affected by being truant. False Negative (FN) gives the outcome at which the model inaccurately predicts the negative category. The condition is not located despite having existence. The Matthews correlation coefficient MCC of each RNN is calculated based on the values of the corresponding confusion matrix:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP) \cdot (TP+FN) \cdot (TN+FP) \cdot (TN+FN)}} \tag{4.8}$$

It can be seen that metric MCC strongly depends on the values of the confusion matrix. As the TP and TN values become larger, the numerator gives higher values. It should be mentioned that the numerator gets a high value just in case when both TP and TN have large values. Based on Lagrange multipliers can be proved that MCC gets maximum value 1 for $(TP, TN, FP, FN) = \left(\frac{C}{2}, \frac{C}{2,0,0}\right)$ where C is the number of elements of the data. Similarly, MCC has a minimum value -1 for$(TP, TN, FP, FN) = \left(0, 1, \frac{C}{2}, \frac{C}{2}\right)$. MCC is a metric of matching the test and predicted sets. It should be noted that metric MCC does not give high value when TN and TN are very different, and FP and FN are not close to zero. F_1 the score is calculated from the confusion matrix, but the True Negatives (TN) are neglected. The formula of the F_1 the score is the following:

$$F_1 = \frac{2 \cdot TP}{2 \cdot TP + FN + FP} \tag{4.9}$$

F_1score is a gauge of test precision and can be explained as both (precision and recall) weighted average [135]. It deals with both the precision and recall of the test to calculate the score. Precision is defined as the cardinality of the correct positive results, which are divided by the number of the whole positive results acquired by the learning model. The recall being the positive class accuracy could be defined as the proportion of pertinent samples that are accurately retrieved. In the learning framework, the precision/recall offers a beneficial intuition on the demeanor of the classifier [136]. The optimal value of the $F_1 the$ score is 1, and the lower in rank is 0. The proportional share of precision and recall are the same to F_1score. MCC is a further trustworthy statistical evaluation, which generates a high score exclusively in the event that the acquired prediction results are good in the whole four confusion matrix classes when the positive element size and negative element size corresponds [137]. MCC is an exclusive rate of binary classification that achieves a high score just if I have a binary predictor that can accurately predict almost all positive data representative cases and the plurality of negative data representative cases [138], [139]. Numerous researchers have a particular opinion considering the exact meaning of F_1score and MCC. Almost all sensible performance with standard measurements represent the ratio across the space separating the number of accurately categorized samples and the gross samples number (for instance, [140]). Two major features distinguish MCC from the F_1score [141], [142].

Chapter 5: Computational and Simulation Results

This chapter presents the assessment results of several RNN model instances produced during this research. Moreover, model extensibility in space is evaluated. The chapter starts by reporting findings and evaluating all models offered. Evaluation results of several RNN models established in this analysis are provided. This chapter contributes supervised data training for timestamped data on which the previously provided chapters' results are given. It is not a straightforward task to extract information from an interplanetary spacecraft mission. Alignment utilizes dissimilarity measures among timestamped data. Then supervised learning models are proposed, accompanied by a threshold scale. The detection approach is also cast as a prediction task using the F1 score and the Matthews Correlation Coefficient (MCC). It demonstrates that it is feasible to the score, notably to include meaningful results and interpretation. Ultimately, experiments on a real dataset are provided. The coverage of the hypotheses outlined in the first chapter is presented in the last part of this chapter.

5.1. Results of the Generic Environmental Models

Since it is not enough to propose a new algorithm, several different computational tests are performed to verify the functionality of the algorithm to ensure that the proposed algorithm is efficient. A decision (classification), or a forecast, is the outcome of an ML process. I need the opportunity to calculate ML efficiency rigorously for accurate and credible usage of ML in these results. Performance evaluation means quality appraisal and computation evaluation, which will allow optimal and accurate ML algorithms for numerous applications to be established. Scientific computing has historically been dominated by complex numerical simulations that are intensive in terms of resources. However, new smart possibilities are generated with the advent of data-driven models and algorithms.

5.1.1. Healthy Residential District Detection Approach Results

As I do not have a timestamp for the collected data, by performing a splitting of data into a smaller range, the storing order of the 2% of the samples gave us the road formation trajectories. This information made us consider that the sampling order matches the data's storing order in the file. Figure 5.1 is generated for multi-directional data analysis to acquire a better comprehension depiction.

The interpretation process provides visual depictions that include a GIS view utilized to produce the spatial contour plot representation. This provides visual relationships between the 3D coordinates of the samplings and the CO_2 emission levels through a parallel contour view.

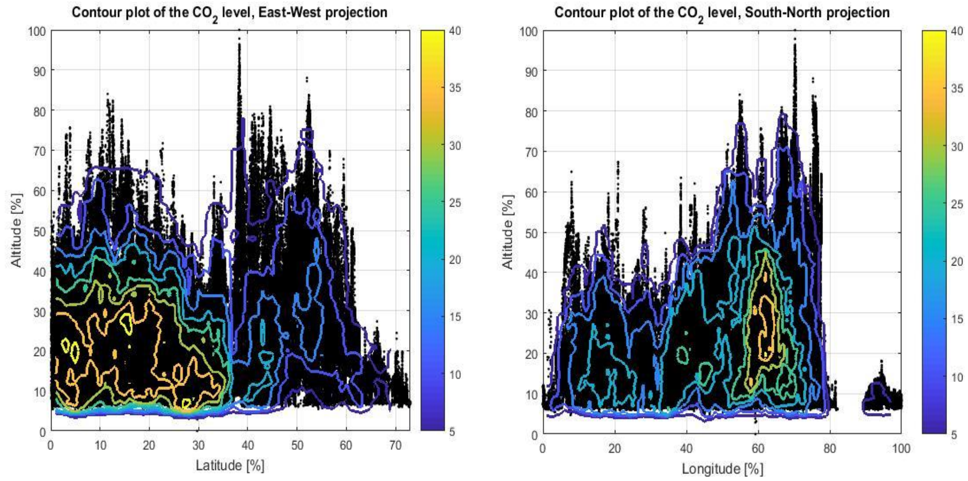


Figure 5. 1: Contour plot of the CO2 level from south-north (left) and east-Ist (right) projection

These figures are sophisticated representations of environmental sensory data sets showing the high number of measurement points, drawing with good accuracy even the map of the peninsula (see Figure 5.2).

Figure 5. 2: Google map view of Peninsula (North Jutland, Denmark)

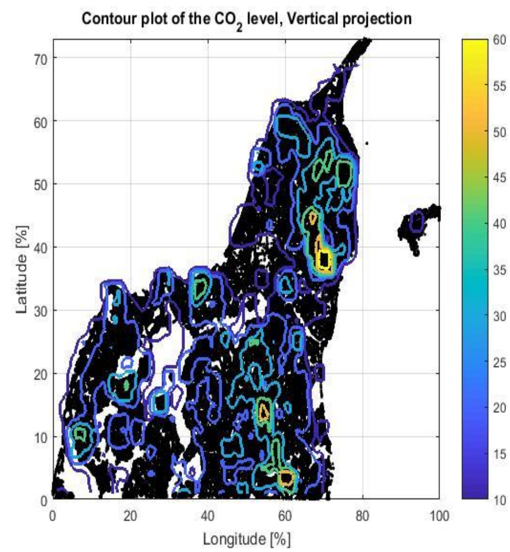


Figure 5. 3: CO2 level Contour plot (vertical projection)

In the model, the yellow contour lines represent a higher emission level, which means more polluted zones, while the blue points represent a less polluted zone and the purple is the least, which are the healthiest residential district to live in. If I compare the contour plot in Figure

5.3 with Google map view Figure 5.2, then it can be concluded that the most affected regions with high CO_2 emission levels are: $R_{10,6}$, $R_{9,6}$, $R_{6,7}$, $R_{6,8}$, $R_{5,7}$, followed by the regions of the green color: $R_{3,7}$, $R_{3,8}$, $R_{9,1}$, $R_{9,2}$, $R_{9,3}$, $R_{10,6}$, then followed with the regions of the blue such as the regions $R_{2,6}$, $R_{2,7}$, $R_{2,8}$, as an example. While the most convenient regions are: $R_{9,7}$, $R_{7,2}$, $R_{8,2}$, $R_{10,3}$, $R_{1,8}$, $R_{1,9}$. Which can be organized as a table below:

Table 5. 1: CO_2 levels and categories

CO_2 level categories	**CO_2 level regions**
Most polluted zone	$R_{10,6}$, $R_{9,6}$, $R_{6,7}$, $R_{6,8}$, $R_{5,7}$
Reasonable zone	$R_{3,7}$, $R_{3,8}$, $R_{9,1}$, $R_{9,2}$, $R_{9,3}$, $R_{10,6}$, $R_{2,6}$, $R_{2,7}$, $R_{2,8}$
Healthy zone	$R_{9,7}$, $R_{7,2}$, $R_{8,2}$, $R_{10,3}$, $R_{1,8}$, $R_{1,9}$

5.1.2. Results of Climate Comfort Detection Approach

When a historical dataset is acquired and investigated, it usually obeys a particular pattern known as statistical distribution, as an example. If 116 years of January precipitation data Ire gathered and examined, the pattern of the data has which composed of the January precipitation as an example having a trend to a very slight decrease that can be concluded by the value of -0.066 over the mentioned period of time, as illustrated in Figure 5.4.

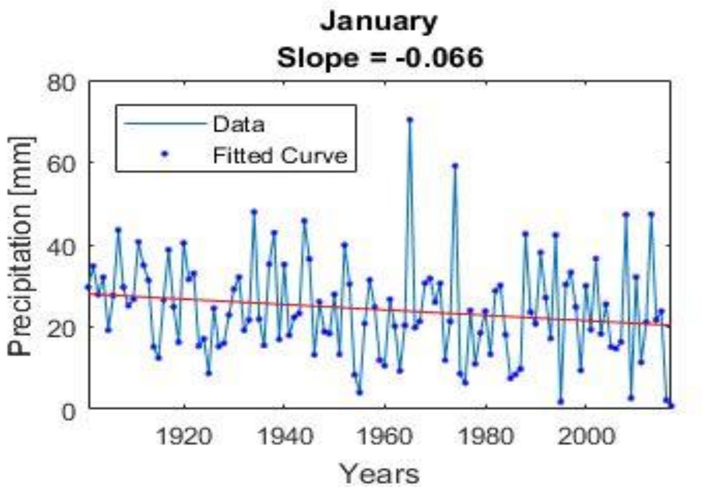


Figure 5. 4: Precipitation-January slope over 116 years

(Data: line of segments; Fitted curve: dots; Trend: red line)

While the average temperature for July shows a slight increase over that period with a slope value equals to 0.020 which can be seen in Figure 5.5. It can be concluded that the average annual precipitation is around 15 inches, and the average annual temperature is around 10.5 °C. It is significant to appraise how climate holds numerous and varied data. The µ monthly precipitation and temperature could be sketched to represent seasonality by month. The next chart illustrates the µ monthly precipitation and temperature for the Jordan region through the period 1901-2017.

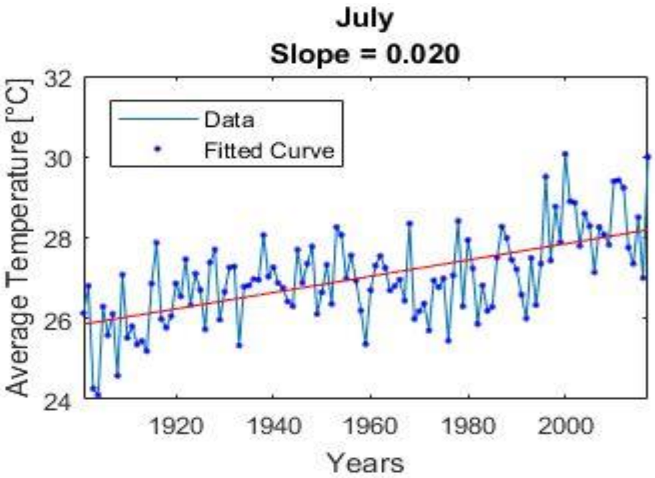


Figure 5. 5: Average temperature-July slope over 116 years (Data: line of segments; Fitted curve: dots; Trend: red line)

According to Figure 5.6 tourism climate comfort condition has attendance in January, February, March, and climate comfort deficiency has shown an unpleasant limit. In April with the instantaneous rise of temperature and reduction of raining.

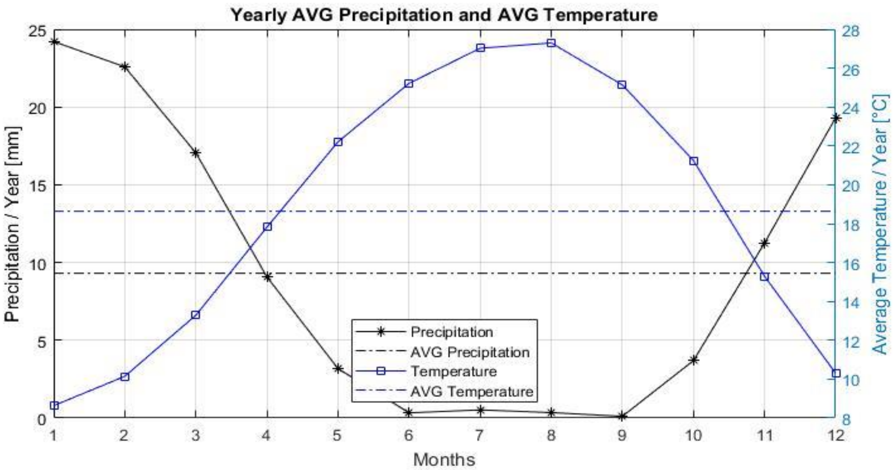


Figure 5. 6: Average monthly temperature and precipitation for Jordan from (1901-2017)

The perfect months for attending tourist from the µ annual precipitation and temperature perspective is May, June, September, and subsequently October. While in November and

December after the subsequent decrease of temperature is prevailing. The following figure shows a temperature fluctuation through the various quarters of years with the minimum temperatures in (January, February) while the highest temperatures are in August, which considered to be the least good or desirable month for tourism in terms of climate in Jordan followed by July due to high temperature which tells that this is a model of mediterranean climate. To show the modification precipitation and temperature in a monthly manner, gridded monthly precipitation/temperature time-series data obtained and utilized to provide a µ monthly/annual climatologies version archive, the obtained monthly modification of precipitation and temperature (1901-2017), is shown in Figure 5.7 this time series illustrates that there is a slight change over the given period.

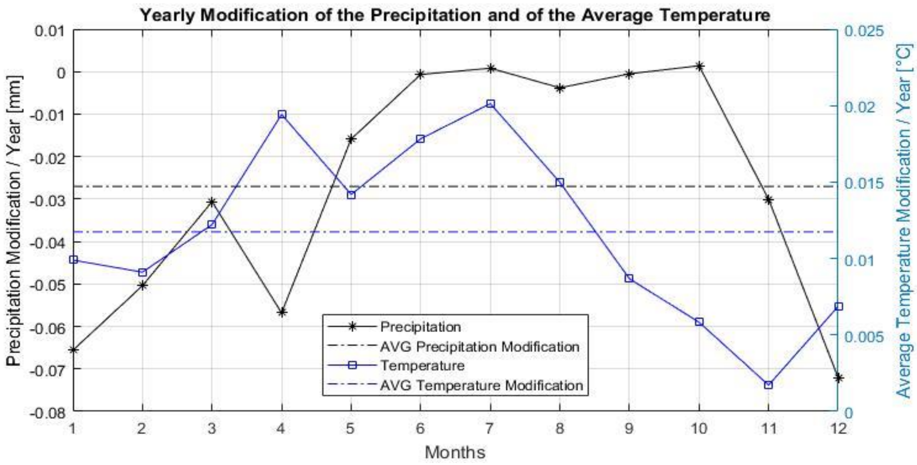


Figure 5. 7: Monthly modification of precipitation and temperature (1901-2017)

The generated Figure 5.8 shows the TCI value of the Jordan area for each month. The scores of TCI are slightly greater in several months of autumn and winter (March, April, and October) rather than other months, correspond to the categorization of TCI distributions, which illustrated in Table 4.1, the prevailing seasonal modality in Jordan is the peak of the winter as it can be seen in Figure 5.8 the maximum TCI score is in April, followed by March, May, and October, while in the summer period (June, July, August, and September), the scores are proportionately weak, so that coincides with the category "Marginal". July is observed as the worst month to conduct any activity for tourism in terms of climate. TCI five sub-indices participate variously to the score of TCI for every month, the sub-indices vary from month to month and the contrasting climatic sturdiness. The maximum TCI score is more than (80) in April, consequently categorizing as having ' excellent' (Table 4.1). Other months such as March, May, and October are in the classification of 'very good', October is the least among them. January, November, and December are considered among the classification of 'good ' It can be noticed that their related scores are nearby to each other. Also, it can be seen that by table 4.1. That June, July, and August fall with the same category in sub-indices value with the subcategory of 'marginal,' while February has the rank of 'good'. There is an indication to mention that higher summer temperatures take part in reduced tourism disbursements in Jordan.

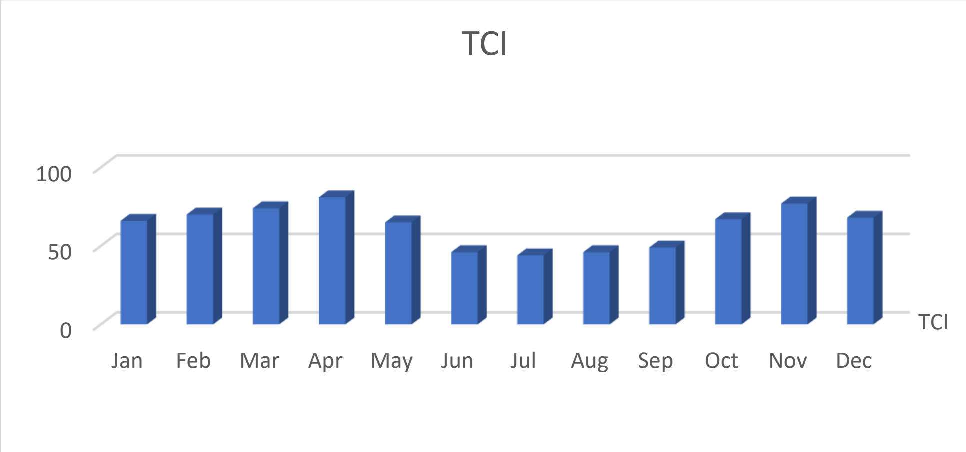


Figure 5. 8: Monthly TCI in Jordan (2011-2018)

It is clear that June, July, August also September possess the greatest hits of temperatures, and this will affect their attendance by having inferior circumstances for tourists based on table 4.1. sunshine and precipitation participate to enlargement of TCI score, wind speed owns the lowest values in the months of the summer, particularly in July and August. Thus, it must be observed that the wind speed to the greatest extent is the undesirable element, as it decreases the score of TCI in summer due to snug wind also in January due to wintry wind.

5.2. Results of the Structured Prediction Model

Sensor technology is important to advance analytics. Sensors generate data signatures requiring more off-line analysis. The ability to detect variance within incoming data is an important track of this model. A robust method for identifying variation is utilized to detect if an event has occurred in a particular image time, based on an assessment made with the taken image timing variables, which include image meantime; capture start/end time of the sample is illustrated in Table 5.2.

Table 5. 2: Inspected mission phases

Phase Name	Start Sample ID	Start Time	End Sample ID	End Time
APPROACH SCIENCE	1	2004-037T02:07:06.498	10,675	2004-162T14:47:05.854
TOUR PRE-HUYGENS	10,940	2004-164T02:33:51.000	31,640	2004-358T13:47:22.548
TOUR	32,032	2005-015T18:28:29.491	166,187	2008-183T09:17:06.323
EXTENDED MISSION	166,188	2008-183T21:04:09.008	235,887	2010-283T14:14:20.741
EXTENDED-EXTENDED MISSION	235,888	2010-285T05:23:32.745	407,303	2017-257T19:59:04.075

Within our analysis, I utilized a three-valued array [X, Y, Z] components of the spacecraft position vector in [km]. Figure 5.9 shows the position in the sampling range: 45000-65000. Timing is connected with every spacecraft locomotion information in an observation.

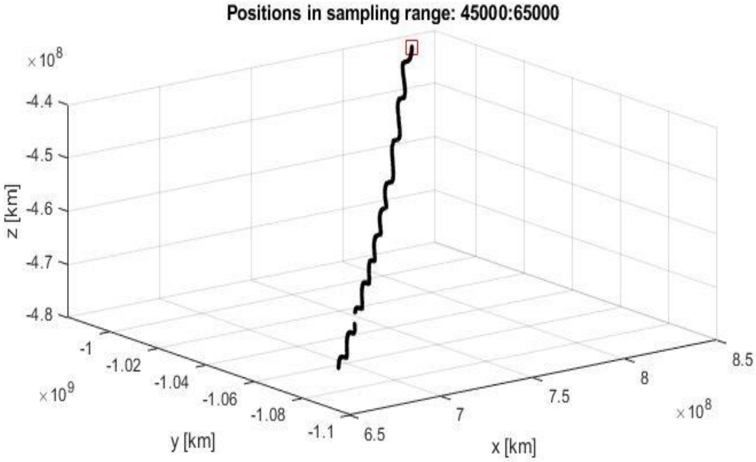


Figure 5. 9: Cassini's [x, y, z] Position

Timing enumerates the whole image events in each stamp and associated start and end times. Time steps offer an additional method to express our time series; the algorithm considers the previous time series's to be as a foretell for the following time step. The model has a total number of layers, which equals 5, the input layer of LSTM has 100 hidden units, while the parameters of the fully connected Layers for numClasses1 = 100, and numClasses2 = 1. LSTM cell has another number of parameters to train our model via Adam optimizer over the max epoch, which equals 100 epochs with minibatch size = 128 and validation frequency = 10 of bracing the performance. There are two fully connected layers. Figure 5.10 represents the velocity magnitude vector change and its histogram.

Based on the previous Figure graph, I have found that the number of velocity magnitude changes during the (2004-2017) C-H project was ~ 10k. The model ends up with a regression-layer to get the final result. To assess the efficiency of our ML approaches for actuating complex events to be specified among large datasets, I have applied the model to reveal the complex events related to velocity magnitude change. The histogram velocity plotted in the logarithmic scale shows the velocity magnitude change over time. The aspect of “learning” with ML indicates the aptitude of an algorithm to notice and learn patterns among data to ameliorate the results, i.e., to utilize the existing data to foretell events and solve the ambiguity. I’m exploiting the LSTM network as our adopted framework.

The LSTM framework input is a sequence such as a sample number, sampling moments, and observations among the intervals. After executing the previous sequencing of temporal modeling, I hand over the output to LSTM. The output is passed into two fully connected layers, these layers are required for generating an eminent representation which facilely provides a discriminate, as closure the LSTM framework is fed to an output regression layer that comprises time steps, each event represents a sample observation that may bring about a complex event.

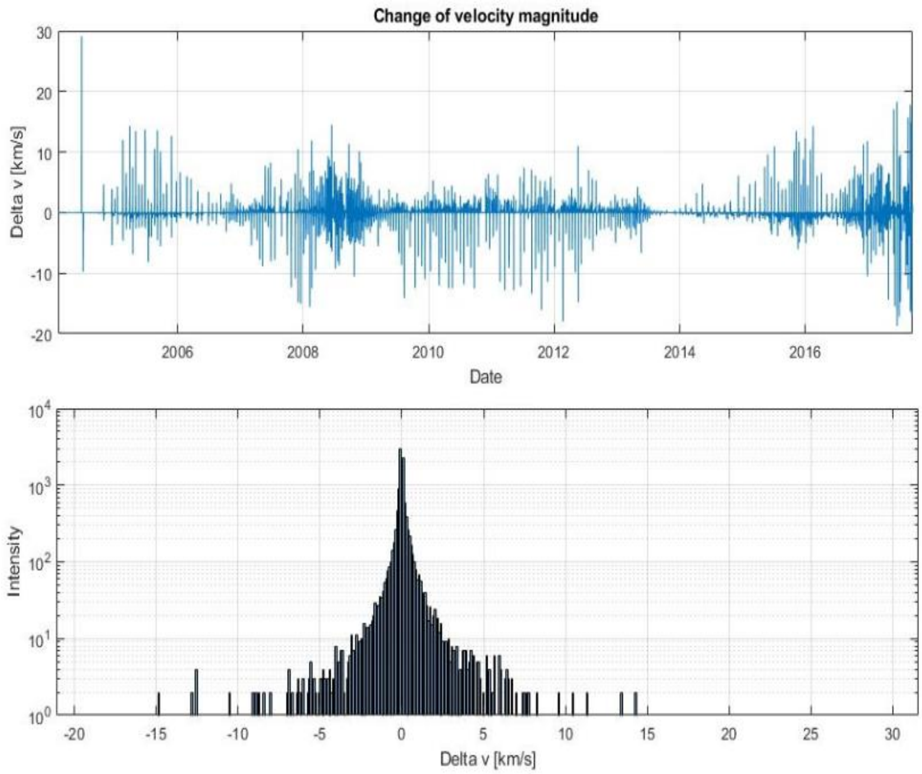
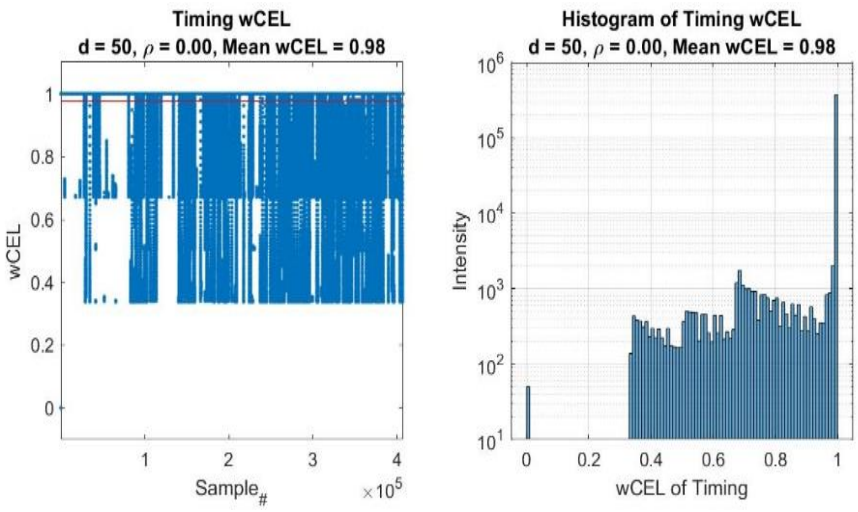


Figure 5. 10: Velocity magnitude change and related histogram over time

Also, the observed variables will represent the features of the samples. The algorithm was able to reveal the related complex events. The main aim behind applying our classifier is to specify complex events from sensory generated data, detect temporal semantics for complex events recognition, and reveal them.

5.3. Results of Special Event Detection and Weighted Complex Event Level Algorithms

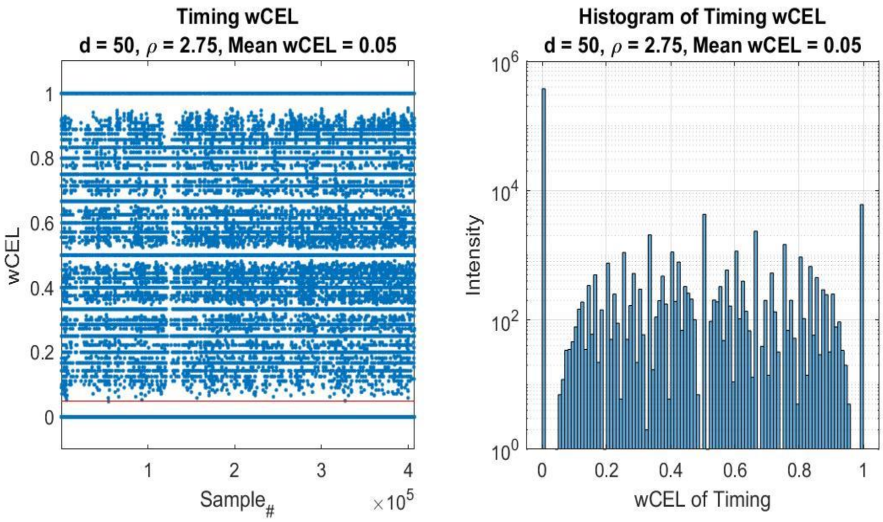
The proposed method has detected a list of complex events through the metric of wCEL among Cassini's image batches, among five analyzed phases of the mission, which include: Approach science mission, Extended mission, Extended-Extended mission, Tour mission, Tour pre-Huygens mission. Fifteen variables of the metadata Ire involved in the analysis process. The selected group of the most remarkable events are listed below (Figure 5.11 - Figure 5.13).



(a) *(b)*

Figure 5. 11: Weighted Complex Event Level, wCEL of timing (d = 50, ρ = 0)(a), and related histogram (b)

In numerous situations, these distinctive events should be processed to understand the phenomenon that stands behind them. The selected list shows that as the values of (σ) decrease, the wCEL increases.

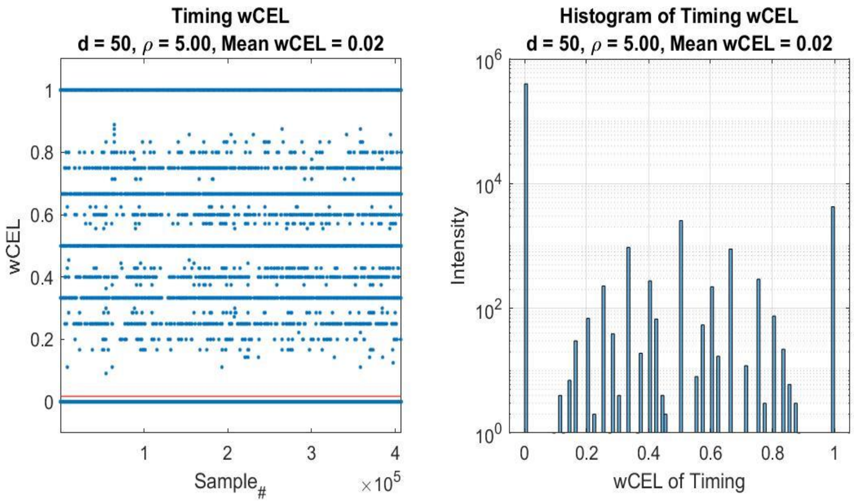


(a) *(b)*

Figure 5. 12: Weighted Complex Event Level, *wCEL of timing (d = 50, ρ=2.75) (a), and the related histogram (b)*

In Group_A (Timing) of variables, three components Ire used for the special event detection:

i) Sampling moment at the Cassini; ii) Shutting time at the Cassini (being the difference between starting and ending moments); iii) Sampling moment at the Earth.



(a) *(b)*

Figure 5. 13: Weighted Complex Event Level, *wCEL of timing (d = 50, ρ=5.00) (a), and related histogram (b)*

Transmission of the samples to the Earth was influenced by Saturn, Cassini, and Earth's relative position causing variable temporal storage durations of the samples at the spacecraft. The µ weighted complex event level with different window sizes for the group (A) is given in Figure 5.14, with the related coefficient of variance. The µ weighted is correlated with an occurrence or result with its consistent quantitative outcome and then outlining all entities together. Based on Figure 5.15, it can be concluded the cut values of the complex event-level detector mechanism for group A of the variables (see Table 5.3).

Table 5. 3: The estimated cut value of the sensitivity of the average wCEL (Group A: timing)

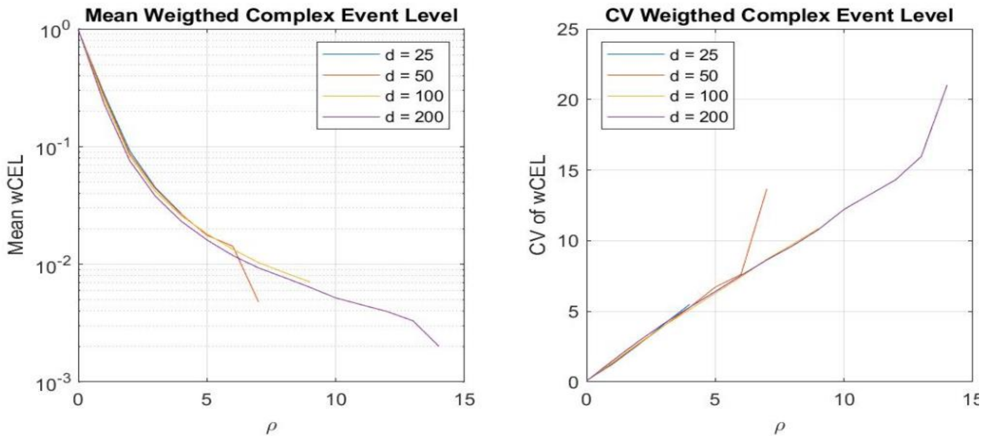
Sample window size (d)	$\boldsymbol{\rho^*}$
25	5
50	8
100	10
200	15

Figure 5.16 represents the estimation of the µ wCEL (Group A) of timing, sampling window, d = 200). It was found that the µ weighted Complex Event Level metric for the timing is an exponential function of an exponential function and has the following formula:

$$mwCEL(\rho) = \begin{cases} 1 & if\ \rho = 0 \\ \exp(-a \cdot \rho \cdot \exp(-b \cdot \rho)) & if\ \rho \in (0, \rho^*) \\ 0 & if\ \rho \geq \rho^* \end{cases} \tag{5.1}$$

where $mwCEL$ is the µ of weighted Complex Event Level, ρ is the sensitivity of the Special Event Detector, a and b are parameters depending weakly on the sample window size (d).

Parameter ρ^* is the cut value of the SED sensitivity and based on Figure 5-15 depends on the sample window size: the greater is d, the greater becomes ρ^*. This phenomenon is caused by the smoothed property of the SED influenced by the moving average function.



(a) *(b)*

Figure 5. 14: Medium Weighted Complex Event Level, μwCEL (Group A), d (sampling window sizes) (a), and related Coefficient of Variance(b)

Estimated fitting parameters a and b are given in Table 5.4 with the coefficient of determination, $R^2 > 0.99$.

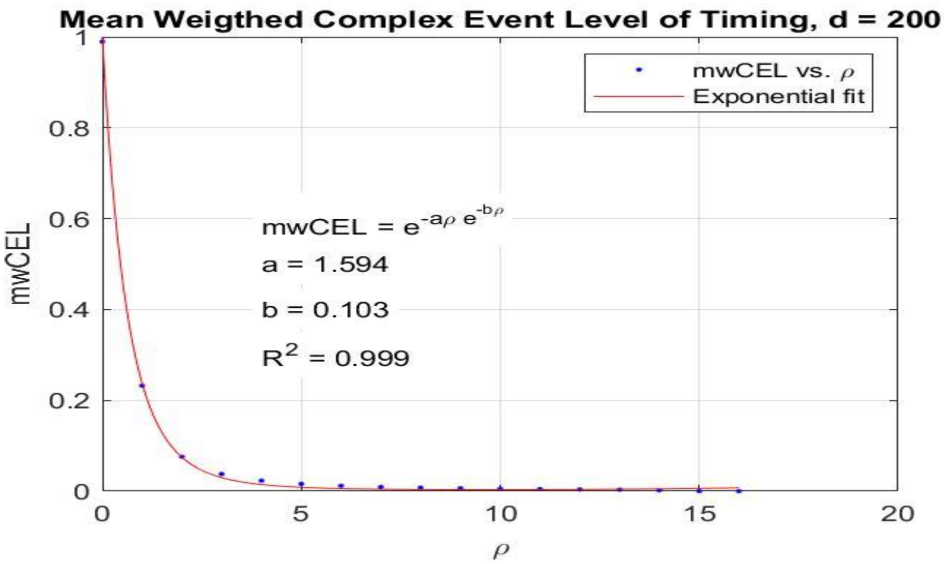
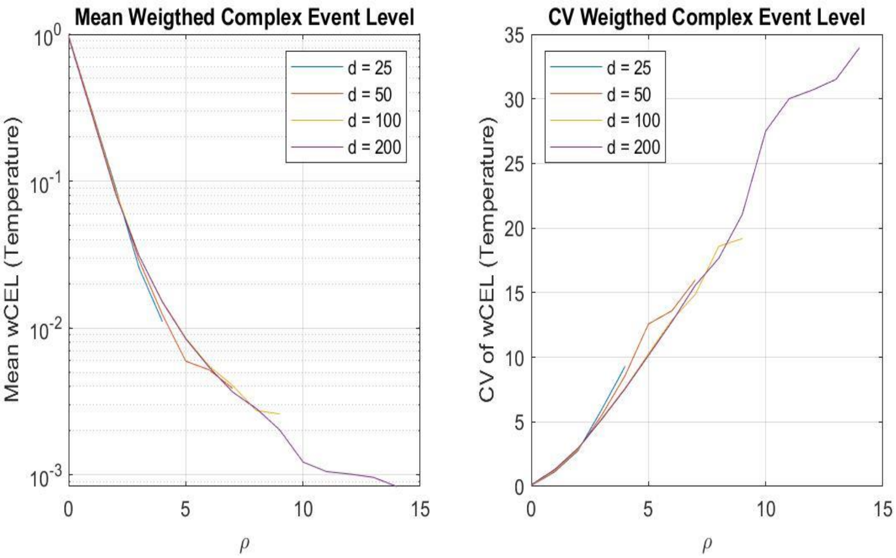


Figure 5. 15: Estimation of the Medium Weighted Complex Event Level, μwCEL (Group A) of timing, sampling window, d = 200)

*Table 5. 4: Estimated parameters of the average wCEL (Group A: timin**g)***

Sample window size (d)	*a*	*b*	R^2
25	1.353	0.070	0.999
50	1.413	0.086	0.999
100	1.483	0.085	0.999
200	1.594	0.103	0.999

In Group_B (Temperature) of variables, five temperature components Ire used for the special event detection: i) Temp. of the optics filter; ii) Temp. of the front optics; iii) Temp. of the rear optics; iv) Temp. of the detector; v) Temp. of the head electronics.



(a) *(b)*

Figure 5. 16: Medium Weighted Complex Event Level, μ wCEL (Group B), d (sampling window sizes) (a), and related Coefficient of Variance(b)

5.4. Results of CKE Approach

The used dataset is downloaded from NASA's jet propulsion laboratory. I'm concerned with the data captured during the period that extends between [16-Feb-2004, 15-Sep-2017], which is almost 13.5 years, where the dataset sample n = 407,303. Figure 5.17 shows sample ID vs. the number of observation and sequences, where the subphases number have an exponential graph, while the number of observations has linear time dependence. I'm interested in these samples as they represent the acquired data after Cassini's spacecraft was inserted into Saturn orbit. Data collecting was carried out within various phases as Ill as sub-phases across the outer space mission.
Every sub-phase also contains many sequences to which every sequence involves a specific figure or quantity of observations based on the judgment of the Cassini imaging team mission and other related teams such as engineering.

The observation includes a series of samplings at which the size of the set counts on scientific events of the orbiter Cassini or outer space events related to the followed path. In addition to the number of observations in the inspected time interval, the sequences were 2,355 and M = 10,850, respectively.

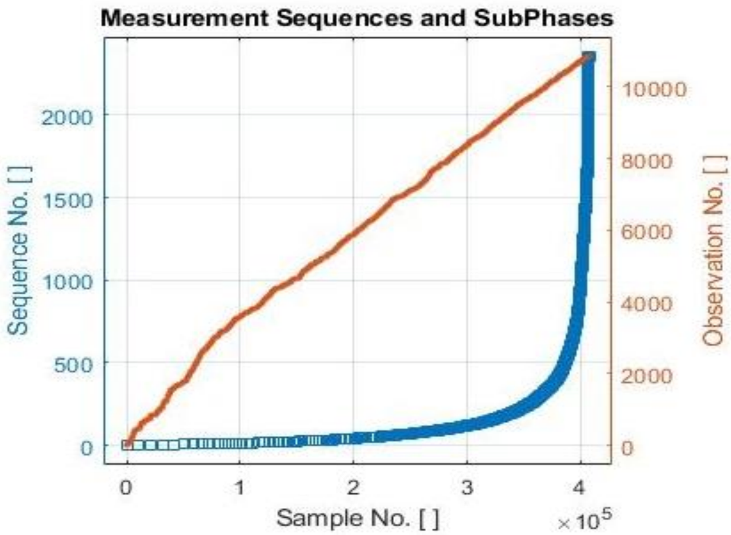


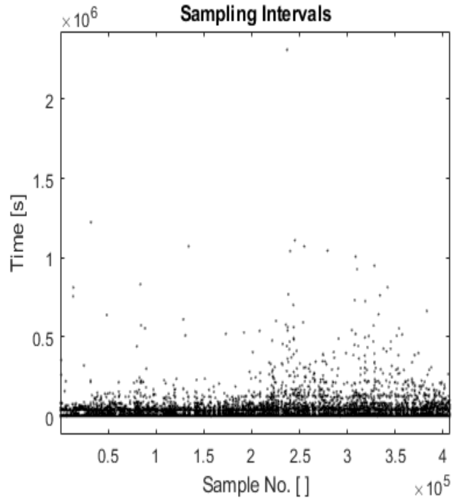
Figure 5. 17: Measurements of sequences and subphase vs. sample number

Potential complex events of the data set are in the moment of change of observation sequences. Within the conducted examination, I utilized a small proportional quantity but a representative group of independent variables ($k = 8$, check Table 5.5).

Table 5. 5: The analyzed list of the independent variable

Var.	Variable Name	Description
v_1	Sampling interval [s]	Time int. between consecutive samplings
v_2	Sampling durations [s]	Duration of samplings
v_3	Detector temperature [°C]	Temp. of Charged Coupled Device (CCD)
v_4	Filter temperature [°C]	Temperature of Wheels filters
v_5	Diff. No. of packets/image	Abs(expected – received) packets/image
v_6	Data Transmission Rate [kbit/s]	Rate of transmitted data by the orbiter
v_7	Image compression ratio [bit/pixel]	Received images compression ratio
v_8	Picture exposure time [s]	Exposure time of picture

The supervised learning process for specifying the CKE technique's operating values for memory size r, the sensitivity of the outlier detection method ρ, and severity threshold Th of the method I used first 1% subset of the total samples ($n_{learn} = 407,3$). The remainder of 99% of the data Ire utilized as test data to validate the CKE analysis model. Sampling intervals and sampling durations are given in Figure 5.18 and Figure 5.19, respectively. Sampling interval and sampling duration will satisfy the time domain necessity. Where the horizontal axis shows the sample number, and the vertical axis represents the time.



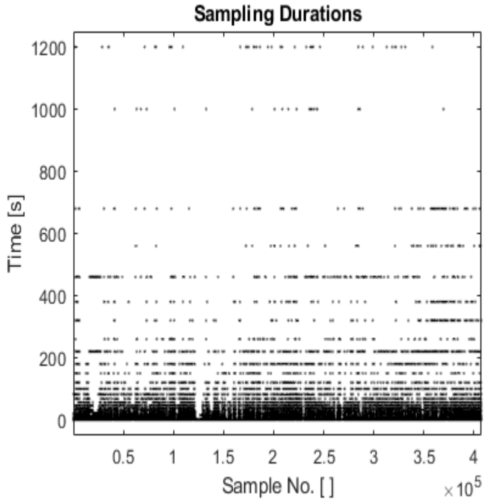
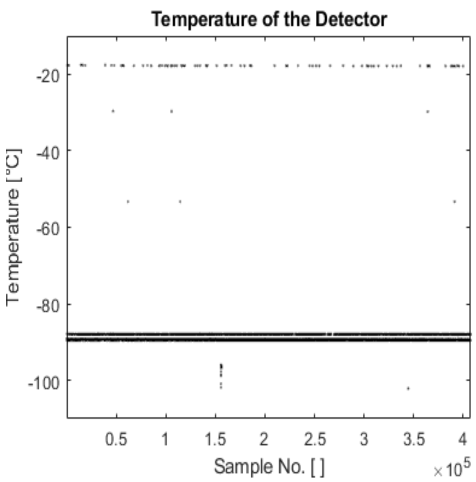


Figure 5. 18: Sampling intervals at CO *Figure 5. 19: Sampling durations at CO*

The sampling time shows the time interval among consecutive samples, while the sampling duration means the difference in time among two successive samples. Under the varied ranges of the temperature for the detector and the filter, it is possible to detect special events by detecting the set of discrete points in the represented data. The investigated detector and filter temperature are represented (Figure 5.20 and Figure 5.21).



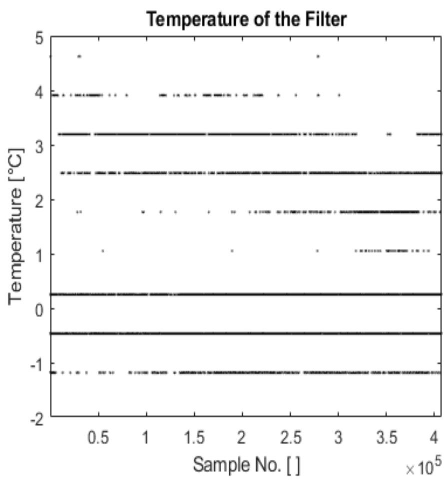


Figure 5. 20: Detector temperature of CO *Figure 5. 21: Filter temperature of CO*

By utilizing DL, I'm training our model to learn the implicit pattern and rules spontaneously. Once the model is trained, I could introduce new data to detect complex events through a black box with an output function based on our proposed model. The proposed model is arranged to vouch that each event observation among the sampling interval will be checked. It can be noticed that the indispensable sampling time is around 15 s or more. The temperature of the detector and the filter is working in very different ranges. It is noticed that the data transmission rate is varied based on the active phase of the mission as the transfer rate ranges between 5 kilobits per second at the minimum rate, while the maximum rate is 365 kilobits per second. The time dependence of the error rate and the transfer rate is given in Figures 5.22 and 5.23, respectively.

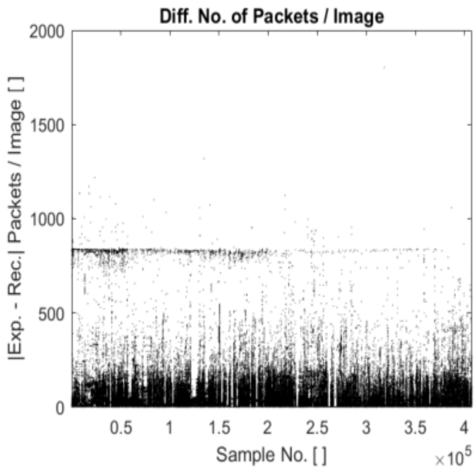


Figure 5. 22: Difference No. of packets/image

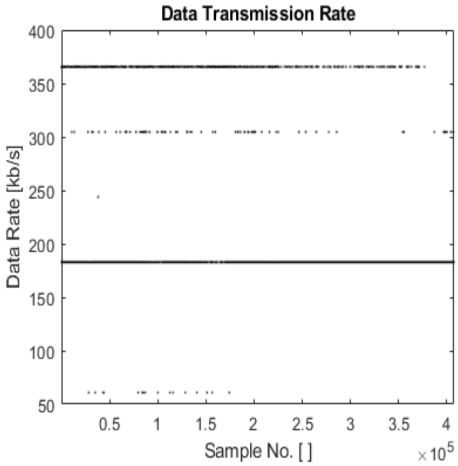


Figure 5. 23: Data transmission rate by Cassini

The model provides the ability to track several observations. In practice, the expected packets and received packets for each image are different because of the image sampling quality.

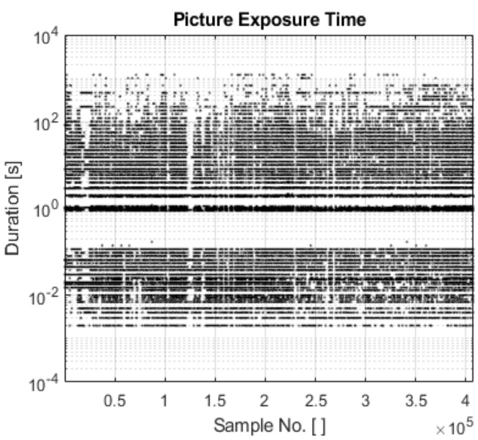


Figure 5. 24: Picture exposure time at CO

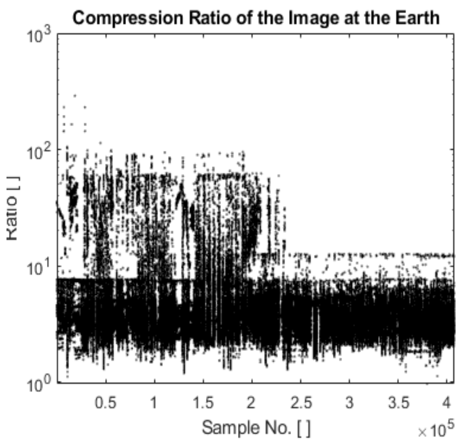


Figure 5. 25: Received images compression ratio

Radio signals shall need between 68 to 84 minutes to make their journey across the space separating Cassini and the ground station on the Earth. It is noticed that the data transmission rate is varied based on the active phase of the mission as the transfer rate ranges between 5 kilobits per second at the minimum rate, while the maximum rate is 365 kilobits per second. The content influences picture exposure time and compression of sampled data at the CO (see Figure 5.24 and Figure 5.25).

The dependence of the CKE method hit ratio on parameters r and ρ are given in Figure 5.26, while the detected special events via the proposed method are presented in Figure 5.27. Through the analysis, it is also expected that there will be several picture exposure times ranging from 0-1200 seconds. Short exposures are used needed to reduce smears throughout close Cassini flybys. The compression ratio extent between 2 and 3 is determined by the data actual entropy. Moreover, based on the running activity, it incorporates different ratios ranging from 2:1 to the ratio of 10:1. The provided AI model qualified us to detect and confirm a considerable number of complex events based on these variations of ratios.

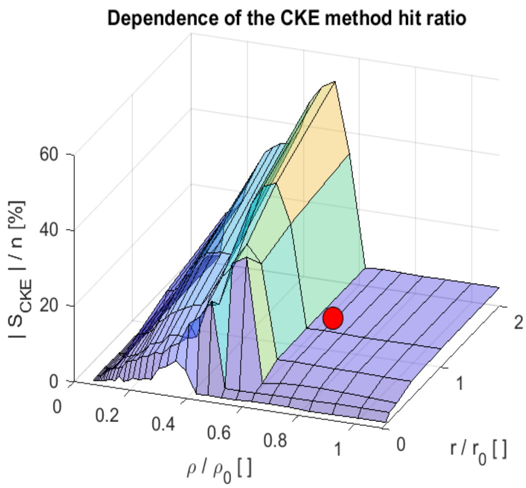


Figure 5. 26: Dependence of the CKE hit ratio on r and ρ

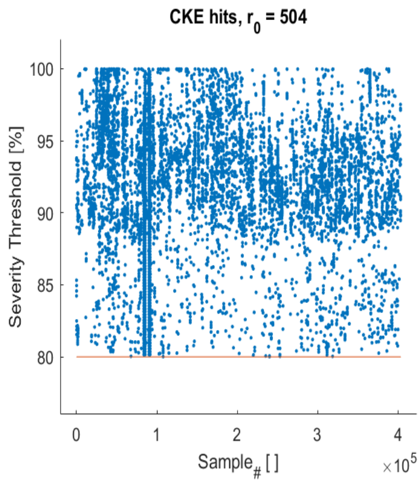


Figure 5. 27: Detected special events by CKE method

For the learning time series of the C-H project, it was found that the optimum memory size is $r^* = 1 \cdot r_0 = 2$ and the optimum sensitivity of the outlier detector is $\rho^* = 0.7 \cdot \rho_0 = 0.7 \cdot (\max(V) - \min(V))/\,\sigma[n, r]$. The optimum severity threshold Th of the CKE method was determined based on the requirement to find the nearest number of special events to the number of sequences ($M = 10{,}850$) executed during the project. The memory size and severity threshold Ire found to be $r^* = 504$ and $Th = 87.6\,\%$, respectively. Resulting in $|\, S_{CKE} \,| =$ 10,134 number of special events detected in the testing data inducing hit ratio of the special events to be $|\, S_{CKE} \,| \,/\, n = 2.4\,\%$.

5.5. Results of Meta-Learning LSTM Approach

The essential considered factors of quantitative image analysis are processing and analysis. Among the challenges that will face any researcher are software and hardware limitations. During our dataset processing and inspection, I encountered these kinds of restrictions. Furthermore, I Ire able to overcome them; as I'm dealing with the Bd, I cannot depend on the regular computer hardware, so I used GPU; they are a hardware appliance that is most effective for parallel and rapid processing. GPUs provide DL with the ability to perform separated computations from the central processor (that is serial tasks dedicated) and adequately fulfilling complex computations. In our research, I will use the GPU to be eligible to process a big data set of Saturn images that contain more than 400,000 images. To initiate the process of training, I indiscriminately sampled 50K images from the adopted dataset volumes. Every image is correlated to one or more categories, arranged in 6 observable denominations, as represented in Figure 5-28. From left to right: Saturn, Rings, Titan, Icy Satellites, Small Satellites (rocks), Sky.

Figure 5. 28: Cassini mission images sampling presenting the adopted content labeling classes

The label selection method is based on each image content, as it is delineated to an interpretative word just as Cassini teams adopted. Below is a screenshot of the classification process adopted above, which shows the image with its target with correct classification accuracy, even with not existing before images. The proposed algorithm is capable of processing at high speed. Also, the effectiveness of the adopted approach to transfer learning is noticed. Table 5.6 shows the adopted classes and the number of images utilized in the primary processes of training and testing.

Table 5. 6: Number of used images for the initiated process of training and testing

Class	**Saturn**	**Rings**	**Titan**	**Icy Satellites**	**Small Satellites (rocks)**	**Sky**
Training Images	9865	8369	9568	7460	7879	6859
Testing images	1983	1870	2120	1987	2060	1580

The framework of meta-learning could be executed to any technique which is trained via the scheme of meta-learning. The purpose is imparting an inclusive approach that can readily be ordered to achieve the best or the desired performance with any required task. The analyses of the cell of tensors are straightforward embedding via the layer of map-reducer discriminator (D), which is acting as a pooling layer that reduces the mapped features. At the same time, the meta-learning LSTM will deconstruct each generated tensor into four cell tensors: (input tensor cell), (forget tensor cell), (cell state tensor cell), and (output tensor cell). Our model complexity is determined by the revelation of Levin complexity definition [143]:

$$C_L(P) = \min_{P} \{cL(p)\text{: if program p solves } P \text{ and then ceases during time } t_P\} \quad (5.2)$$

where
$$C_L(P) = 1(p) + log\big(t(p)\big) \quad (5.3)$$

The problem that needs to be solved is represented by P, while l(p) is the program p length, and t(p) represents the time that is consumed by p to solve P. Transferring knowledge acquired from a single task with the abundance of labeled data to some other tasks with slight labeled data, the level of progression of performing its mission relies on how pertinent is the former task of big-scale image recognition to the current task [144]. In the situation of meta-learning LSTMs, with the epilogue of each task, the experience is gained and kept in the memory of the LSTM cell. To confirm the proposed model efficiency, this model is set to weigh with other commonly known methods of image classification.

Table 5. 7: A comparison among prior relevant work

Model Name	**SVM [145]**	**Random Forest [145]**	**Fuzzy Clustering [146]**	**Optimized Fuzzy system [147]**	**SIep Image Transfor-mation Technique [148]**	**Gray Level Cooccur -rence Matrices [149]**	**Our Prop-osed Model**
Accuracy [%]	52.6	72.3	88.78	93.07 and 95.25	93.34	90	**96.7**

The conducted experiment results are demonstrated in Table 5.7, where it is evident that SVM and random forest models notably have less accuracy than the other models.

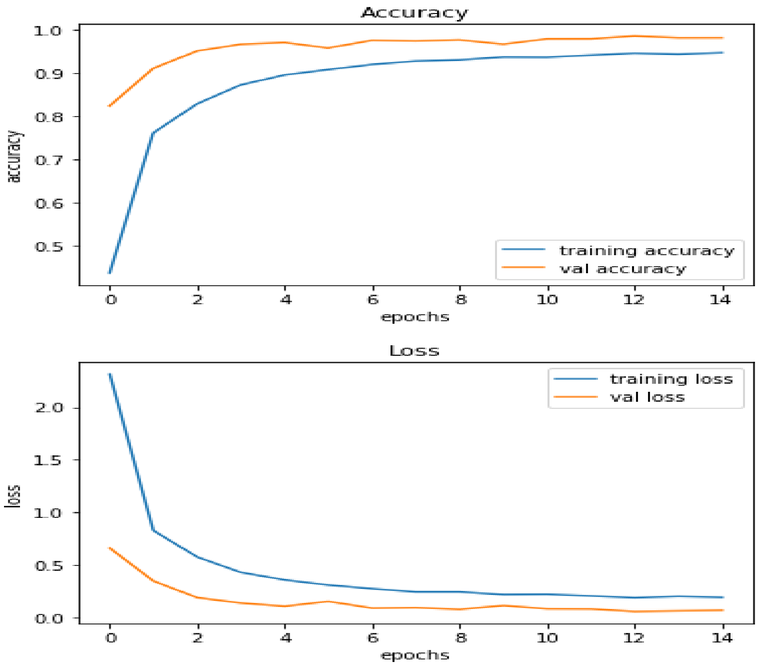


Figure 5. 29: Plot representation of the model accuracy on train, validation

The justification of this lies in the emphatic feature extraction performed by our provided model. Also, our model adopts DL within its optimal optimization and parameter initialization. Figure 5.29 shows the diagram of training accuracy versus validation accuracy over the number of epochs. By measuring the model's accuracy, I can determine how effective it is performing. To get to desirable accuracy, I choose to decrease loss across the network, but not only on the validation range. Within the loss plot, it is clear that the model holds a comparable efficiency on the training data and validation data. The produced errors may be evaluated by a given model with a confusion matrix or its confusion degree. If the model gets confused, the confusion matrix can record the confusion.

Figure 5. 30: Plot representation of the model confusion matrix

The confusion matrix for calculating the overall classifier accuracy is shown in Figure 5.30, which is evaluated using the 50 thousand images dataset. The acquired percentage is 96.7%. The confusion matrix is a particular table structure that actually describes the algorithm's efficiency. Each column depicts the instances in a real class, while Every row in the matrix describes the instances in a class expected (or vice versa).

5.6. Results of Detecting Trajectory Modifications Approach

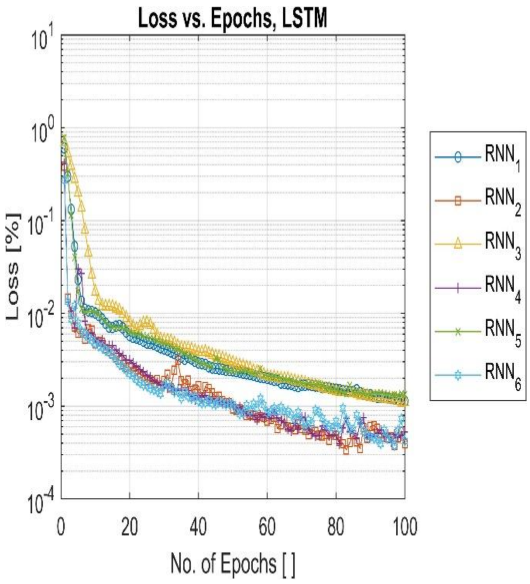
DL models specifically learn nuanced, task-adaptive, and high-level data functions. DL is a key supporting interpretation technology. These models briefly present the key principles utilized in contemporary deep neural networks, based on approaches that have proved useful for detecting trajectory maneuvers modifications. The resulting learning time and the detection accuracy of these networks are given in Table 5.8. The results obtained show that a DL approach applied is an excellent approach with high accuracy. There were executed training and evaluation of the test data sets of the trajectory in the last 13.5 years of the Cassini project with three types of RNNs with six different hyperparameter settings for each of them, which makes eighteen neural networks in total. Six of them are LSTM, and six are BiLSTM networks, while the last six are GRU. The changing input parameters (mini-batch size, number of hidden units, number of classes on layer three, and layer four).

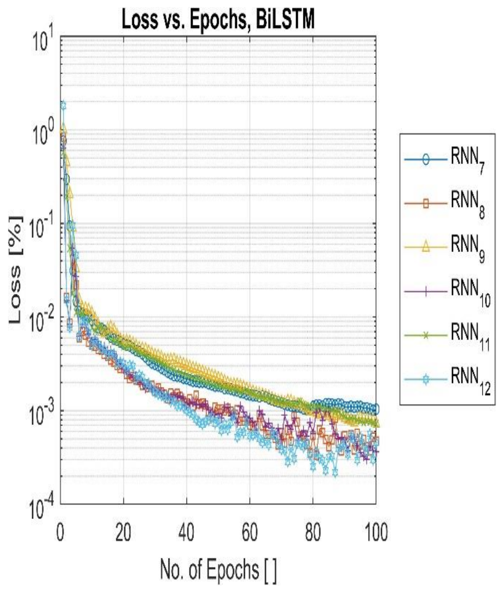
Table 5. 8: Detection accuracy of the trajectory modification of different RNNs

System	RNN Type	Mini Batch Size [ ]	Hidden units$_{\#}$ on L2	Classes$_{\#}$ on L3	Classes$_{\#}$ on L4	Learning time [s]	Detection accuracy [%]
RNN_1	LSTM	2500	10	100	2	799.5	97.42
RNN_2	LSTM	2500	100	100	2	1352.5	97.13
RNN_3	LSTM	5000	10	100	2	965.1	98.58
RNN_4	**LSTM**	**5000**	**100**	**100**	**2**	**800.2**	**99.19**
RNN_5	LSTM	10000	10	100	2	1469.9	98.63
RNN_6	LSTM	10000	100	100	2	992.4	98.97
RNN_7	BiLSTM	2500	10	100	2	802.9	99.65
RNN_8	BiLSTM	2500	100	100	2	1489.6	96.43
RNN_9	BiLSTM	5000	10	100	2	1014.0	99.75
RNN_{10}	BiLSTM	5000	100	100	2	817.5	98.09
RNN_{11}	BiLSTM	10000	10	100	2	1497.4	99.68
RNN_{12}	BiLSTM	10000	100	100	2	1175.8	99.90
RNN_{13}	GRU	2500	10	100	2	986.5	99.92
RNN_{14}	GRU	2500	100	100	2	818.9	99.98
RNN_{15}	GRU	5000	10	100	2	1015.8	99.63
RNN_{16}	**GRU**	**5000**	**100**	**100**	**2**	**817.8**	**99.98**
RNN_{17}	GRU	10000	10	100	2	1550.3	97.60
RNN_{18}	GRU	10000	100	100	2	1036.7	99.95

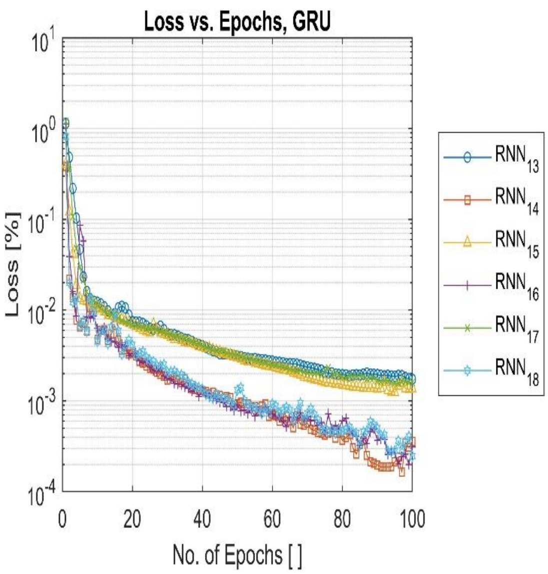
Learning is done in streams of batches, which suggests that a number of training cases are sent across the network, and the results, known as forecasts, are gathered. The loss is measured and recorded for each batch, which shows the total mistake. It is evident if accuracy improves, the loss decreases. Visualization of the loss during the learning process is represented in Figure 5.31. The less is the number of hidden units, the higher is the loss. It can be observed that the number of hidden units on L2 influences the learning loss. For ten hidden units, I get double the learning loss. Similar behavior has it the RNN networks, it can be noticed that RNN_{12} becomes over learned for 100 hidden units on the L2 layer. The ideal learning rate is bound to be subjected to the loss of the leaned behavior of the data, which in its role is relying on together the used dataset and the architecture of the model. The value of the loss denotes how deficiently or efficiently the model is conducting after each iteration of learning.

The learning deficit is doubled when there are ten hidden units. Analogous feature is observed on the LSTM, BiLSTM and GRU networks, but the last two seems to become over-learned after utilizing one hundred hidden units on the layer of L2. I have trained the framework until it has completed 100 epochs and displayed the training loss values vs. the epochs number. The improvement in the loss, as seen in Figure 5-31 reflects the progress in training. As the amount of epochs rises, the loss of training is reduced. As compared to other LSTM networks, RNN_4 LSTM has the lowest loss. RNN_9 is offering the highest outcomes in terms of losses among the other BiLSTM networks, and GRU_{16} is offering the highest outcomes in terms of losses among the other GRU networks.





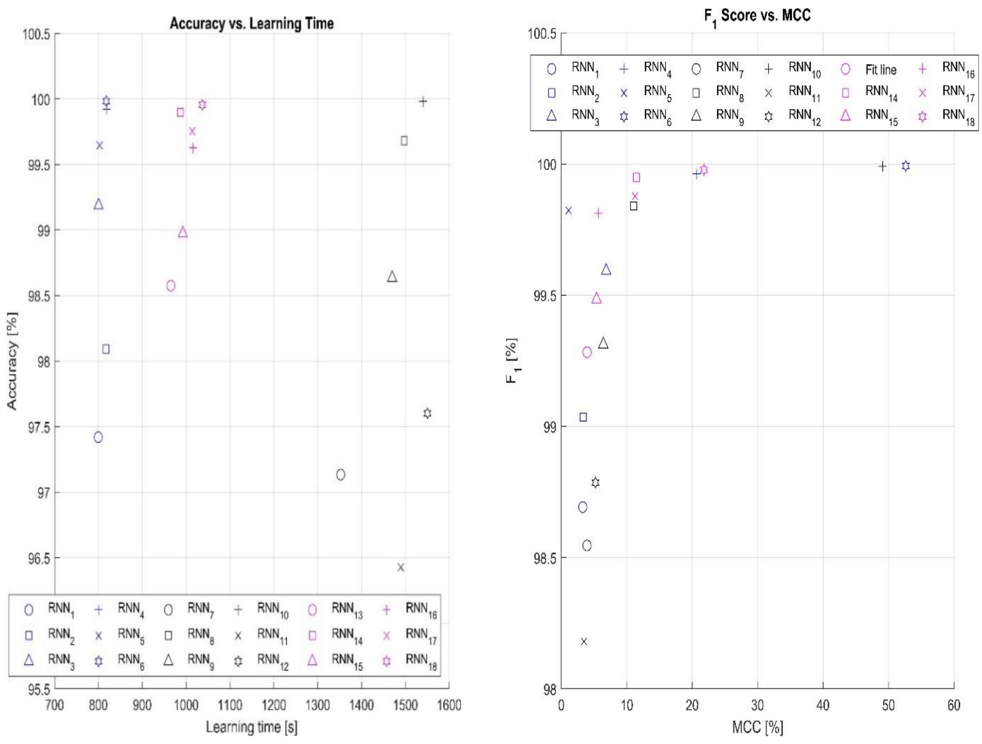
(a) *(b)*



(c)

Figure 5. 31: Minibatch learning loss dependence on the number of epochs (a): LSTM; (b): BiLSTM (c): GRU

The accuracy metric is utilized to quantify the algorithm functioning in an explicable method. Generally, the model accuracy is specified after calculating the used model parameters with a percentage style. It is considered as the model accuracy measure that represents the model prediction contrasted to the correct data. The ideal learning rate is unavoidably revealed to the data's lack of learned behaviour which is dependent on both the dataset and the model's design. The loss value shows how successfully or incompetently the model works during each learning iteration. It is evident in the Figure 5-32a, that RNN_4 LSTM and RNN_{16} GRU are offering the ideal accuracy when set side by side to other RNN network models. It depicts the relationship between accuracy and learning period with each of the RNNs studied. Most of the GRU network need less time to learn than BiLSTM and LSTM networks. Several epochs are frequently used to train the network. I refer to an epoch as a time where all of the training data has been screened exactly once. Thus, 100 epochs correspond to 100 iterations over the same training set.



(a) *(b)*

Figure 5. 32: Plot of RNNs learning time and accuracy(a); Dependency of the F_1 score MCC (b)

The accuracy measure is used to calculate the model in an explainable way. The accuracy of the model is usually is based on the values that are calculated by using the model parameters are defined. It is known as the algorithm accuracy metric, reflecting the algorithm forecast in reference to the right data. All LSTM networks need lower learning time than BiLSTM networks. The dependency of the F_1 factor on the MCC Matthew correlation coefficient is given in Figure 5-32b. Having different calculation formula of performance metrics, I used multiple metrics to evaluate relation between detection accuracy, MCC and F_1 score of the analysed data series.

Model precision implies the number of classifications that a trend accurately forecasts, divided by the total number of predictions produced by a model correctly predicts. It is a way to measure mode results. The model accuracy is identified after calculating the used model parameters with a percentage style; this is clear in the figure above. As an illustration, RNN4 is hitting an accuracy that exceeds the value of 99.9 % with a minimum learning time. Mathew correlation coefficient MCC and F_1 score of the resulting neural networks is given in Table 5.9. The following is a list of RNNs in tapering order for the MCC metric: RNN_6, RNN_{10}, RNN_{18}, RNN_4, RNN_{17}, RNN_8, RNN_3, RNN_9, RNN_{16}, RNN_{16}, RNN_{15}, RNN_{12}, RNN_{13}, RNN_7, RNN_{11}, RNN_2, RNN_1, RNN_5.

Table 5.9: Mathews correlation coefficient MCC and F_1 score of the analyzed RNNs

RNN	**1**	**2**	**3**	**4**	**5**	**6**
Type			**LSTM**			
MCC [%]	3.27	3.36	6.85	20.69	1.12	52.63
F_1 [%]	98.69	99.04	99.59	99.96	99.82	99.99

RNN	**7**	**8**	**9**	**10**	**11**	**12**
Type			**BiLSTM**			
MCC [%]	3.92	11.06	6.42	49.09	3.47	5.22
F_1 [%]	98.55	99.84	99.31	99.99	98.18	98.79

RNN	**13**	**14**	**15**	**16**	**17**	**18**
Type			**GRU**			
MCC [%]	3.94	11.46	5.38	5.69	11.28	21.80
F_1 [%]	99.28	99.95	99.48	99.81	99.88	99.99

Through observing this outcome, it can be concluded that the optimal RNN to recognize the modification among Cassini trajectory is GRU accompanied by 100 hidden units and a MiniBatch of 5000 and is able to model trajectory change behaviour with 99.98% precision, with very little time fewer than 13.7 minutes on a desktop machine with 12 central processing cores, and 64 GB of RAM.

5.7 Hypothesis Coverage

The hypothesis of a dissertation is a declaration focused on the idea a researcher is investigating. The most important aspect of scientific research is a dissertation hypothesis, as it is a testable prediction statement about which a researcher is building during the research process. The hypotheses described in the first chapter (Section 1.4, page 5) and their acceptance and coverage are stated in this section via the earlier models implementation.

Hypothesis Statement	Explanation
Model as abstract as practicable and as comprehensive as required.	The paradigm is straightforward adequate that the reasonably simple dataset does not overfit. Moreover, the neural-branch model architecture facilitates a simple expansion and convergence of a new collection of inputs and outputs by adding new target framework and configuration divisions. However, the model must be trained and the hyperparameter calibrated for that specific dataset.
Modeling can be based only on data-space input and output and applied rapidly	Once trained, without having any infrastructure from the actual framework, the RNN models run standalone.
The model will manage different forms of input and output signals: binary, persistent, step-like, repetitive, etc.	The implemented sensory data experimental setups cover different kinds of signals—the resistor issues binary signs. The sensor temperature monitor generates continuous signs. The photodiode generates a step-like signal, depending on the LED voltage levels. Analysis of RNN-based models with several output layers will simultaneously model many signal forms.
When the unseen data is transmitted to the framework, the model shall be able to reproduce the framework in the test process	The implemented experiments have shown that it can accurately predict unseen before data.
The models should not over-fit the training results, must be capable of functioning effectively in the implementation process with the latest inputs.	All of the findings and graphs produced show that the proposed models did not overfit. This indicates that it would not attempt to fit the data's noise and generalize to new data well.
The provided algorithms find optimal solutions with less computational effort than optimization algorithms, iterative methods, or simple heuristics.	Based on the acquired result and the needed time for learning, it can be assured that the proposed models have less computational effort with optimal solutions.
It is hypothesized that the establishment of balance among completion time and increasing efficiency is done using optimization methods.	The obtained results confirm that the balance is confirmed among the efficiency and completion time.
For the up-to-the-model, a threshold value should be established in which the prediction error may be predicted.	Threshold values have been established to satisfy the hypothesis
It is hypothesized that; the proposed algorithm must be scalable and can be performed in polynomial time and ensures convergence to the optimal solution. This means that it does not stick in local optimums.	The results and conducted analysis show that the provided models do not stick in local optimums.

Chapter 6: Thesis Overview

This chapter aims to provide a fundamental understanding of the thesis overview to the doctoral thesis. It offers a brief overview of the research focus or problem, explains why this study is worth conducting and discusses how it will be completed. A full listing of each thesis can be found in the thesis booklet.

6.1. Preface

In this debate, structured ML prediction is considered and precisely, those involving sequential structure. It is focused on the relatively mature methods of complex event processing, which is associated with the identification of complex events focused on domain specialist rules and trends, while the meta-learning LSTM and Constructive Knowledge-based Event (CKE) algorithms can provide better analyses of vast volumes of data within a small-time interval and supervised learning via structured machine-learning prediction. This dissertation focus on the specific issues prompted by structured outputs when the object involved in a ML task has a complex event processing, prediction, or multi-class classification where the goal is to predict several outcomes from some set to an instance.

I present my structured ML approaches to learn specific similarity measures for change-point detection. Analyzing the interplanetary trajectory is a big part of Saturn's task research as rapidly linked tools, and sensory devices become part of our everyday lives. The high-velocity knowledge flow sea is rising. This vast amount of high-rate data generated demands rapid insight in numerous applications such as the Internet of Things, energy storage, etc. This produces the need for Complex Event Processing (CEP) frameworks, utilizing articulate state-of-the-art approaches to collect qualitative details. The Mission of Cassini, as an illustration, generated more than 630 gigabytes of research-based data that include 450,000 taken images. ML assists the experts and researchers with data enclosed by this vast extent. This dissertation uses the Cassini dataset as a particular instance of analysis to illustrate the remarkable capabilities of introducing Artificial Intelligence (AI) among space missions to extend further intelligent computing. It is intended to consider exploiting Deep Learning (DL) on the space missions evolution platforms, offering higher efficiency and reliability. Using DL classifiers with diverse data volume access, it is illustrated that incorporating the collected spacecraft data with machine-learning approaches, which is fundamental for obtaining scientific significance. Based on these findings, the provided models on incorporating space sensed data into AI scope earmarking supervised classification concerning planetary data, which expresses a path incorporating Cassini spacecraft mission data into ML. The techniques of DL can be utilized to evolve intelligent solutions. Over the past several years, massive progress adoption of AI techniques with special attention on neural networks has appeared globally. There has been a generous dash in the AI scope to provide robust solutions in numerous fields. Models focused on Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM), Bidirectional LSTMs, and Gated Recurrent Unite (GRU) are exceptional in learning sequences and capable of capturing long-range dependencies in the temporal data collection. In this analysis, various LSTM and GRU models are used to model the Cassini–Huygens' outer space mission.

This work employs Cassini's planetary mission data and environmental events to build DL classifiers. It is also demonstrated that amalgamating the generated spacecraft data ameliorates the performance and delineation of ML approaches, which is fundamental for obtaining systematic purport.

6.2. Statement of the Issue and Motivation

Science research focuses on two pillars: data collection, which utilizes computations, tests, and/or observations to produce new measures of complicated phenomena; and data processing, which seeks to derive new information from the data. Historically, much of the work has been to gather evidence, for example, beginning with the push to build telescopes to study planets and finishing with large-scale, multi-physics simulations to obtain a glimpse into potentially inaccessible processes, such as supernovae. As data size and sophistication grow, the risk of missed breakthrough opportunities may also intensify and will potentially impede development dramatically. To overcome this problem, several research fields shift. In the evolution procedure of complex systems, interdisciplinary teams of scientists and engineers are engaged. Frequently, such teams are established by inter-institutional collaboration.

More data-driven approaches eventually seek to eliminate the need for assumptions and replace them with meticulously tailored theories with extensive data collections. This data explosion is not restricted to research applications. Digital revolution and the accompanying capacity to record anything, from banking transfers through internet sales and social networking communications, have revolutionized ML. This revolution was propelled by the availability of massive, labeled data sets propelling the creation of modern ML approaches. These methods enable computers to conduct several challenging tasks. Systematic ML is a central component of AI and cognitive science that can be learned to increase or automate human abilities with scientific evidence and analytical research. Scientific ML will change science and analytical analysis. Investments in large data from science missions, tools for predictive modeling and algorithms, high-performance computing systems would allow breakthroughs and significant change. Incorporating a variety of Deep Learning (DL) models, from the unpretentious to the more sophisticated, in addition to differing datasets, will provide insights into the essence of the data produced by the underlying spacecraft-generated data. DL applications in space science and big data analytics are both the high focal point of data science. This set of methods has been confirmed to be competent to swift and enhance both essential and empirical research. I implement a comprehensive overview and examination of the most up-to-date research in this scope.

6.3. Methodology

CEP is a meta-framework of techniques, e.g., filtering events, matching event patterns, timing analysis, a hierarchical abstraction of events, creation of complex events, the definition of event hierarchies) for processing event flows in real-time and abstracting humanly understandable and actionable knowledge from such event flows. By comparison, AI has experienced colossal development in its potential definitions from its initial inception. AI will also use CEP systems or event streaming platforms to process incoming events and feed them into neural networks. The CEP stream processing logic preprocesses input data chronologically preceding other smart components and allowing them to execute tasks they may otherwise not have been able to perform. The summary of this work is divided into six main parts discussed below:

The presented theses outline the experimental setups used to test the research hypothesis. Sensory data are explained, and their dependencies are identified with each other. The theses realize the methodology to satisfy the theories. It discusses the adopted work methodology. It presents and describes numerous phases in the execution of the methodology aspect. It illuminates the preparation of training data and shows the neural network's design and other technical information.

The first thesis is concerned with adopting remote sensing as a tool to detect climate comfort and modeling the events as 3D+ spaces (having at least three dimensions, such as spatial and temporal). For each sensor, one may determine qualitative events dependent on sensor measurements (e.g., temperature, humidity) and different degrees of granularity for each merit (e.g., day-month-year for the period).

The second thesis propose method identified a collection of complex events using the weighted Complex Event Level (wCEL) metric across five evaluated phases of the Cassini project, namely the Approach science, the Extended mission, the Extended-Extended mission, the Tour mission, and the Tour pre-Huygens trip. In the analysis process, fifteen metadata variables were included.

The third thesis provides the element of learning and reasoning with structured prediction based on revealing event complexity is given, whereas the task of revealing complex events encompasses modeling special events that are structurally associated. The put forward algorithm is intended to learn the prospective functions of reasoning with structured prediction based on revealing event complexity, an amalgamation of outstanding conceptual nonlinear features conveyed by regression models.

In the fourth thesis, the Constructive Knowledge-based Event (CKE) algorithm is introduced, which provides associate degree creative methodology of CEP to fully develop process patterns or events counting on the constructive feature computing. I presented a constructive event detection technique to find situations when the event’s statute has transferred over a special event to a complex event by generating an emphasis centerpiece on complex interconnection components by utilizing stacked bidirectional Long Short-Term Memory (LSTM) networks.

The fifth thesis presents the Meta-Learner LSTM algorithm; it speculates an essential topic related to the classification of remotely sensed images, in which the process of feature coding and extraction are decisive procedures.

The sixth thesis allocates a sophisticated in-depth learning approach for detecting Cassini spacecraft trajectory modifications in post-processing mode. The model utilizes the ability of Recurrent Neural Networks (RNNs) for drawing out useful data and learning the time series inner data pattern, the proposed approaches cast the learning as a structured prediction, one with losses adequately designed for the task: the F1 and Matthews correlation coefficient.

Chapter 7: Conclusion and Applicability of Results in Practice

Hereby it is assumed that the RNN-based models can generalize various events complexity analysis, and with significant precision, it can forecast the realistic new data. Through the design, implementation, and outcomes of the RNN model, the thesis work criteria identified in this report's first chapter are successfully fulfilled. The research centered on comparatively novel RNN implementation of the structured prediction and event complexity analysis and modeling. RNNs are an ideal method for sequence modeling and have been frequently used in the temporal sequence modeling tasks involving outer space mission data, images, etc. The research work results indicate that when properly designed, RNN models with memory unit’s LSTM and GRU can accurately predict various types of sensor values for the defined range, with more than 96% of the classification principle and 99% of the modification detection.

7.1. Conclusions

Benefiting in the field of health environment could be acquired when the GIS method is utilized via sensory data sets, however, refinements have to be made in both the quality and quantity of the available inputs of data for these available methods to guarantee the improved geographical context of health representation via the used maps. Based on these observations convenient inferences between healthy residential districts and environmental elements could be acquired. The major implementation of GIS in the field of health informatics includes health risk analysis, but the method represented in this paper gives a remarkable solution to enhance the quality and adequacy in the field of healthiest district identification algorithms. Climate and tourism are convoluted; climate has an influence on tourism by a direct or indirect route. The outcomes presented that utilizing the ANN model in specifying TCI is a robust approach conferring the curiosity of a low error rate. This research provides that the preferable time of the year to entice tourists to come to Jordan is April, followed by November and March. The climate patterns are changing perceptible, rain ranges are less equally spread, while the temperature augmentation is widening.

CED is an affluent research field accompanied by several aspects to be investigated; the exploitation of learning techniques to classify and detect special events offers a considerable perspective to be utilized either on the environmental data or incoming outer space expeditions, as the vast distance between the spacecraft and the Earth stations requires relatively a lot of crucial time, so the response to a particular event may not be accomplished within the needed time interval.

This dissertation provides a novel model to analyze the time-related multivariable flow of events and demonstrate to insert complex events recognizable proof with constructive reasoning vis utilizing stacked bidirectional LSTM networks. Based on the learning subset, the self-evident utility of CKE recognizable proof shows that just 93.4 % of the sequence changes executed during the C-H project generated special events. This phenomenon is caused by the high number of relatively short and similar sequences performed in the project's last months. More evaluations are planned to identify and explain the CKE method's dependence on the distribution of the special event in time. The proposed models show immense promise for intelligent identification techniques, as it expedited and simplifies the dynamic analysis of the big data within a reasonable short time.

The detection method of C-H spacecraft trajectory modifications has been performed via LSTM / Bi-LSTM/GRU networks. As far as I know, this research is the first one, which deals with detecting the events of spacecraft trajectory modifications. Decisively, I show that our test analysis specifies even though the LSTM models with certain parameters establish the right choice for predicting Cassini spacecraft trajectory modifications. Their employment and extra stacked layers generate a noticeable boost in rising the detection process performance. It is worth indicating that the used models can be comfortably extended to include a considerable scientific area related to the prediction. With more specific information, the provided models present a robust processing step in employing the inner features and time-series- representation via the utilization of LSTM time dependencies for precise detection. I found with our results that concerning binary classifications, MCC presents a further explanatory and veracious score than the F_1 score does. The proposed detection model can identify trajectory modifications of the CO with 99.98% accuracy.

The intelligent framework should consider including an anomaly detection scheme to address this issue, which I have accomplished via exploiting unsupervised algorithms to capture these extreme events or outliers. For this, a further sophisticated DL model should be developed. Among the collected data, images captured by the orbiter are considered as the primary data origin, while the considerable defy is how to recognize and read the correct fact and information from those images.

ML promotes discerning frameworks that are ambidextrous to generalize from the formerly perceived examples. Conventionally, ML has engaged with the extrapolating resolution, which reached after consideration, just like in classification, or on the situation of regression, when I perform a scalar prediction. Structured prediction transacts with dependencies for inter-associated and organized output spaces. As an alternative to viaduct the space among ML frameworks and innovative deduction techniques, I could express the variables set in a fertilized method by providing an appropriate reasoning and training framework.

Planetary remote sensed data has attained a data volume amplitude where the process of putting a decision or plan into effect; requires ML implementation as a logical path of scientific fulfilment. This thesis discussed how ML could be used to explore science questions within the constraints of common characteristics of space physics data. Care should be taken when adapting automated methods to planetary science data due to spatio-temporal difficulties. However, until now, the scant focus was paid to planetary data assessments relative to other areas.

In this work, the dissertation addressed two questions regarding framing ML applications to planetary details. First, considering application efficiency and accuracy is critical. Second, growing the interpretability of ML systems for planetary space missions. For specific ML models, efficiency may be improved, but interpretability increases along with handling characteristic data challenges in this application. To end, I introduced a structure for integrating planetary scope knowledge into ML. This paradigm targeted growing interpretability and resolving spacecraft data aspects of ML for planetary space data. It solves defiance such as the Spatio-temporal features of spacecraft and other common geoscience data problems. The supervised classification method was built on flux data from the Cassini spacecraft to Earth. As ML becomes more common, collecting large quantities of data and label data becomes more necessary, particularly for state-of-the-art neural networks. Machine-learning, natural language interpretation, and computer vision groups related to this topic – mainly on data marking methods, including semi-supervised learning and adaptive learning. Recently, in the Big Data period, the data processing group often responds to various sub-problems in data collection, data labeling, and current data enhancement. The analysis techniques can reduce the spatial ambiguity, and associated challenges regarding the diverge of terrestrial references. The sampled values in the Big Data scale of the C-H planetary project have been analyzed to make a more apparent orientation on the mission phases. A new combinatory meta-heuristic algorithms CKE, Meta-learning LSTM, structured prediction, and DL method of detecting trajectory modifications, Ire introduced. The research issues and the major contributions which have been made in this thesis are summarized as follows:

- In chapter 1, the concept of complex events in the context of IoT integration by remotely sensed data is provided. These areas are supposed to have a significant impact across all aspects of research.

- Chapter 2 provides the background information needed to understand the concept behind the dissertation. Starting with the theoretical background, the chapter develops in detail towards state-of-the-art technologies. The chapter highlights some interesting work done in the study field by other researchers.

- Chapter 3 discusses the research framework methodology. The chapter presents and elaborates on numerous actions to conduct the dissertation. It shows the training-data planning process, the neural network design, and other technical information.

- Chapter 4 provide the analysis of the methodology. It gives a complete and clear the data analysis and justification

- In chapter 5, To assess our approaches' efficiency, the proposed algorithms are benchmarked and evaluated on a comparative study to validate the findings with other algorithms. Simulate the suggested algorithms and show the experimental findings. The evaluation findings show vital precision and tiny learning time for the suggested approaches.

7.2. Applicability of Results in Practice

Nowadays, AI and the underlying computing systems are more than just technical matters; they are matters of state and culture, governance, and public interest. It will affect the decisions that technologists, politicians, and societies create in the next few years will help define how various devices and humans are based upon one another. Technology has progressed dramatically in the last ten years or so, though. Machine-learning algorithms have advanced, especially with the development of neural networks-based DL. Over the past few years, more computational power has been possible to train larger and more complicated models; this has advanced graphical and particle processing systems. The new generation of these processors would boost training capacity even more. The vast volumes of data being produced and now accessible to train AI algorithms are other prominent factors. The consequence of system-level advances has been some of the improvements in AI. A significant part of the recent AI knowledge has been the result of development in the discipline known as DL, a collection of techniques designed to incorporate computer training focused on artificial neural networking. AI can enhance organizations efficiency in many ways, including ML, where neural networks can automatically process vast volumes of high-dimensional data from audio and images

Throughout technologies and logistics, AI can improve distribution routing of transport links, raise fuel effectiveness, and decrease send. A call center utilizing AI in speech recognition is a powerful method in call centers. It's possible to use a mix of consumer demographic and purchase data and social network tracking to classify customers and suggest goods. There are numerous realistic AI usage cases and applications that can be used in various industry areas. Furthermore, many of these applications can be used in many different high-tech systems and enterprises. As one example, the DL techniques strengthen standard analytics techniques, especially utilizing the latest approaches on a wide variety of domains. The most considerable economic influence of AI would undoubtedly be labor market impacts, including replacement, augmentation, and labor efficiency contributions. AI will also fuel creativity, allowing businesses to grow their top line by targeting underserved customers more efficiently through current goods and developing completely new products and services over the longer term. AI would therefore build favorable externalities, promote more effective cross-border exchange, and improve the utilization of useful cross-border data flows. Such rises in economic activity and wages may be reinvested in the economy, thus leading to further expansion.

7.3. Future Research Directions

The new aspect of this work is the concept and the criteria for event detection and creating the whole workflow as an agenda for potential event detection research (from sensing and event extraction methods to operations and decisions centered on the extract events). The structure and comparison provided earlier open the door to explore using ML to address planetary and space project expeditions. Cross-disciplinary work will significantly improve these applications in the future. Particularly as regards interpretability to scientific conclusions by spacecraft-informed or model-adjusted ML. Having planetary science and DL domain awareness in data science implementation enables the pursuit of fundamental questions. I find that adding physics-based knowledge enhances interpretability and boosts the overall efficiency of science-based ML applications.

Future data collection methods may be enhanced. Currently, input and objective data vectors are built until all goal values are found. Therefore, the data collection rate is the same as the data processing rate of the experiment (disregarding latency of the contact channels). This set-up works up to a certain degree where the number of targets is smaller, then where the time-lapse noise is slightly lower in the network, and the model can accommodate it. One alternative may be to establish a data sample rate beyond the contact channel and create input and aim samples at an arbitrary frequency and change values when obtained from the sample and retain the previous value while there is a channel delay. While working with signals from a hardware device to model the underlying outer space generated data, it is conceivable that one must deal with variable sampled data generated asynchronously by various sensors at any point in time.

Publications

List of Own Publications Referred in the Dissertation

1. **Ashraf ALDabbas** – Zoltán Gál – Mohamed Amine Korteby: 3D GIS - A Major Step Analysis to Evaluate Convenient Healthy Residential District Based on Environmental Sensory Data Sets, *9th Hungarian GIS Conference and Exhibition, Debrecen, Hungary.* May 24-25, 2018,

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   http://www.jatit.org/volumes/Vol98No24/18Vol98No24.pdf **(Q3: IF 0.628)**

7. **Ashraf ALDabbas**, Zoltán Gál: Learning and Reasoning with structured Prediction Based on Revealing Event Complexity, International Journal of Advanced Science and Technology, pp 13816 - 13828 Vol. 29 No. 3, 2020. ISSN: 22076360, 20054238. http://sersc.org/journals/index.php/IJAST/article/view/31723. **(Q4: IF 0.41)**

8. **Ashraf ALDabbas**, Zoltan Gal: Cassini-Huygens Mission Images Classification Framework by DL Advanced Approach, *International Journal of Electrical and Computer Engineering.* Vol 11, No 3, 2020. ISSN 2088-8708. *DOI: http://doi.org/10.11591/ijece.v11i3.pp2457-2466.* **(Q2: IF 2.3**)

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13. Gal, Zoltan, Mohamed Amine Korteby, and **Ashraf Dabbas**. "Impact of the delay tolerance in wireless sensor networks: Buffer occupancy and energy consumption aspects." In *2018 IEEE International Conference on Future IoT Technologies (Future IoT)*, pp. 1-8. IEEE, 2018.
14. Mohamed Amine Korteby – Zoltán Gál – **Ashraf Dabbas**: Impact of the Geographic Map Based Movement on the Communication Quality of Sensor Networks, *9th Hungarian GIS Conference and Exhibition*. Debrecen, Hungary. May 24-25, 2018,
15. Gal, Zoltan, Mohamed Amine Korteby, and **Ashraf ALDabbas**. "Estimation of the Wireless Sensor Network Performance using Fractal Behavior of the Generated Cognitive Harmonic Waves." In *2018 9th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, pp. 57-62. IEEE, 2018.
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